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Individual Differences in Stress and Coping: Testing a Model of Decisional Control

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Abstract

Quantifying the processes of coping is one way to make the concept both descriptive and testable. Decisional Control (DC) is a formal, mathematically-specified, normative model which prescribes that an individual faced with a variety of alternatives in a stressing situation will attempt to minimize objective and perceived threat of an adverse event inherent within their choices. In this study, a game-theoretic probability mixture model created for DC was evaluated using established indexes of model fit to empirical decision and choice data. Sources of empirical departure from the fully normative model predictions, notably individual and group cognitive mapping of choice linked threat, were investigated in part through the use of psychometrical profiling of individual differences. Results of a repeated measures ANOVA showed that individualized mappings of subjective threat significantly improved model fit over that of the consensual and objective mappings. Additionally, psychometric profiling did not identify notable trends in model operation.

Keywords

Stress and coping, mathematical modeling, decisional control, threat reduction.

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1.1 Introduction

Coping with stress is a universal experience and one which requires a complex interplay of cognitive functions. Coping with stress can be done in a variety of ways, but choice is key in determining how an individual will respond (Averill, 1973; Thompson, 1981). Through behavioural, cognitive and decisional means, choice in stressful situations offers an advantage of accessing less-threatening alternatives and greater control of reducing stress reactions (Averill, 1973). Dissecting how individuals judge alternatives, when faced with a host of aversive events of varying degrees of undesirability or harm, and exert personal control to minimize the anticipated stress can increase our understanding of the cognitive underpinnings of stress. To understand the role of coping and stress reduction, arguably we must first discuss how a decision maker (DM) formulates a choice (Thompson, 1981).

Beginning with a discussion of normative decision theory, accepted theories and their relevance to our model will be introduced. Particularly, the distinction between normative and descriptive models in decision research will be elucidated. Following this, a normative model of Decisional Control (DC) will be presented in detail along with its underlying game-theoretic architecture. Finally, planned model testing and fit will be discussed as it pertains to necessity testing. When speaking of necessity testing, a distinction from sufficiency testing is needed. The primary goal of the present study is to explore sources of differential conformity between our collected data and the theoretical predictions posited by our formal normative model. While a secondary aim of this research is to understand how psychometric correlates may relate to the operation of the model, the primary interest lies in examining sources of improved fit (necessity testing). Such sources include the historical distinction between objective and subjective properties of stressor processes at an individual and group level (Heukelom, 2008; Rappaport, 1983). Specifically, I examine if there is conformity or departure from objective utilities imposed by the environment and whether improved model fit is observed when taking into account the representation of the environment by the individual (subjective utilities; elaborated on below). Lastly, the aim is not to see whether the model does so (leaving a non-significant empirical departure from model predictions) sufficiently or to improve model fit, but to examine tendered sources of improved empirical fit to predictions.

1.2 Normative Decision Theory

Beginning in the 1950s, cognitive psychologists began focusing on two questions: how do people make decisions and how should decisions be made (Edwards & Fasolo, 2001). While related, the two questions frame decision-making in two separate ways. The first is concerned with what choice is made (the final result of a decision), while the latter incorporates notions about a DM’s use of cognitive mechanisms in explaining how the decision is reached.

The second question is also concerned with the final result, but in this instance the process involved in making the decision becomes the focus. A driving force behind this area of research stemmed from a pursuit to improve decision-making ability through understanding how individuals judge between alternatives (Edwards & Fasolo, 2001). In order to separate the two concepts, the terms normative and descriptive were applied to decision-making theories.

In a descriptive theory, the source of interest is how people make decisions. These theories are descriptive of the process (from presentation of a dilemma to the choice made). Theories concerned with how a decision should be made are referred to as normative. The emphasis of normative theories rests on understanding or explaining how a DM incorporates environmental demands and intellectual tools available to help make the best possible decision. The idea that a best option exists and that it should be the goal of a decision is prescribed by a normative approach. In short, a normative model could be viewed as one with a hypothesized arsenal of cognitive tools used to estimate and incorporate environmental demands in the process of making a decision. On the other hand, a descriptive model expresses how the underlying arsenal is actually appropriated to lead to a decision. It does not attempt to explain which components of the arsenal exist or how they function together to lead to the decision made.

To identify and quantify the “best” choice under a normative theory, cognitive psychologists interested in decision-making rely on mathematics and three specific rules which encompass normative decision theory (Edwards & Fasolo, 2001). The three rules are multi-attribute utility (MAU) measurement, Bayes’ theorem of probability theory (hereafter referred to as Bayes), and maximization of expected utility (Max EU). Each rule will be discussed in turn to an extent that is relevant for understanding its role in the present research.

1.2.1 Multi-attribute utility (MAU).

In order for an individual to make a decision there must be a choice between two or more options. Generating the list of available options can be cognitively taxing as the number of options available to the DM grows. Sometimes the list of options is exhaustive and fully specifies directly what outcomes occur when selected (e.g., in a quantitative closed form solution). An example of this could be choosing what to eat at a restaurant. When you order something off the menu, that selection will be what you receive. Commonly, what occurs instead is that events beyond the DM's control combine with the options available to determine what outcome occurs. An example of this second case could be choosing which route to take home from work and its impact on your trip time. You might choose to take the highway instead of a variety of side-streets, find it unfortunately deadlocked (an event beyond your control), resulting in a very long and unexpected commute.

In normative decision theory, the options available are called "acts" and the events beyond the DM's control are referred to as "states" of the environment. An important element of states is that they are considered mutually exclusive and exhaustive of one another; states and state selection have no effect or relation to other non-selected states. In order for a DM to make a choice, the outcomes comprised of acts and states require some sort of comparable value relative to one another. To be measurable and comparable, they must all share the same measurement scale. However, all assessments of value are entirely subjective of the DM and can vary from one individual to the next. In this respect, all outcomes are considered subjectively different and are referred to as "utilities" in normative decision theory. MAU is the process of aggregating utilities to create an overall subjective score for choice comparison.

However, subjective utilities are not always the only type of utility present. Sometimes there can be objective utilities; utilities which possess the true ranks of outcomes. For example, someone might subjectively appraise their choice of braking at a yellow light as less likely to lead to an accident than choosing to go through the intersection. Objectively this may be false if statistics quantitatively illustrate that it is three times more likely that an accident will occur if they choose to brake. Problems can arise in real world scenarios like this and have consequences for the DM. In this case, a normative model would subscribe to the best objective utility to choose (going through the yellow light), but a descriptive model might find that selection is made using a subjective utility evaluated highest by the DM (braking at the yellow light). To investigate which conditions are operant under the normative model, subjective and objective utilities must be considered and compared (Heukelom, 2008; Rappaport, 1983). More on this topic will follow in subsequent sections on model testing and fit.

1.2.2 Bayes' theorem of probability theory.

In addition to subjectively evaluating utilities, most decisions have a degree of uncertainty to them. Decisions may lead to one or more outcomes beyond the DM's control. However, DMs often have varying degrees of information about the possibility of one outcome or the other. This information permits judging of the probabilities of the outcomes related to that choice, such as in instances where Bayes' theorem can be implemented. Bayes' theorem assists in choice selection by incorporating prior evidence to help in assessing the probability of a particular outcome (Bayes & Price, 1763). DMs use this process known as "fallible inference" or "inference under uncertainty" (Edwards & Fasolo, 2001) to make judgements regarding which outcomes are likely to occur for any given act under a particular state. Using our above traffic example, if the DM had been rear-ended multiple times when choosing to brake at a yellow light, they may have updated their belief to now believe that going through the intersection is best. The prior information that they bring into the decision influences their beliefs and, in this case, their subjective utility aligns with the objective utility. However, if the DM had never been rear-ended braking at an intersection and had done so hundreds of times, they may hold an incorrect belief that their subjective utility is the best choice. Even when additional information is introduced, such as explaining that statistics show it is less optimal to break at the light, it is possible the DM may hold their subjective utility higher still. Further exploration of this and similar concepts is beyond the scope of this present research and related to psychological heuristics (Kahneman, Slovic, & Tversky, 1982).

Relevant to this study is the notion that judging between utilities does rely on prior learned, experienced, or provided knowledge.

1.2.3 Maximization of expected utility (Max EU).

Combining aggregates of relevant utilities and probabilities leads us to a quantitative basis upon which acts can be ranked by DMs. As both utilities and probabilities are subjectively determined by DMs, normative decision theory refers to the aggregates of both as “subjectively expected utilities” (SEUs). Max EU is the process of maximizing the desired outcome by selecting the act with the largest SEU value. Specifically, the last rule dictates choosing the act with the highest utility when outcomes contain no uncertainty and choosing the act with the highest SEU when uncertainty is present (Edwards and Fasolo, 2001).

While this normative theory is a large oversimplification for generating a decision, as undoubtedly a number of cognitive processes are present in each step of the process, it acts as a good referent for the present work. A very thorough review of the literature can be found in Edwards, Miles, and Von Winterfeldt (2007) and Von Winterfeldt and Edwards (1986). It should be evident, however, that through the exploration of these three rules, the process by which individual DMs come to make a decision is largely subjective and can require the use of a variety of cognitive processes. Particular individuals may favor careful selection of acts, desiring a large amount of information prior to choosing one, while others may be more resigned to have a selection delegated to them. Two decision-making strategies related to these sorts of differing approaches are maximization and satisficing. In maximization, a DM exhaustively considers all acts in order to find the one with the best utility, whereas a DM adopting a satisficing strategy will evaluate acts until they find one that is suitable (Simon, 1956). Choosing a satisficing strategy does not disqualify the possibility that the DM was able to apply the three rules of normal decision theory, but decided the effort was not justified to exhaustively search for the objectively best utility. Nor does choosing a maximizing strategy assume that the DM will choose the objectively best utility, as their subjective utilities or their application of the three rules may be flawed. Clearly decision-making is an individualized process likely informed by a variety of dispositional factors. So too is the act of coping to reduce stress.

1.3 Decisional Control

DC is a method of coping with stress in which the DM positions oneself in a stressor situation so as to avoid situational components harboring higher probabilities of threat (Lees & Neufeld, 1999, p. 185). The underlying assumption is that a DM, when faced with a selection of varying levels of subjectively adverse events (acts), will make probabilistic judgements (arguably a cognitively-intensive process) about the threat inherent in each situation (states). The DM then makes a choice to pursue the act they believe has the lowest level of stress associated and best chance for a favorable outcome. Notably, this normative model is well positioned in normative decisional theory and follows the three rules discussed earlier.

As normative models make use of mathematics to discern MAX EU, it is facilitative to start with a practical example that explores the environmental framework and begin introducing some of the equations used in the DC model.

1.4 Environmental Framework of Decisional Control

Stress can range in severity (from benign to behaviorally and/or cognitively paralyzing) and can be evoked by a number of different scenarios (from adverse social events to situations with a chance for severe discomfort or physical harm). Many real-life scenarios can be drawn on to construct elements in a game-theoretic infrastructure composed of stressful alternatives. According to Rasmusen (2007), a game-theoretic infrastructure is one in which the following four elements must be present: a player (or players), information and actions available at each decision point, and the payoff for each outcome. Routed in game theory (Von Neumann & Morgenstem, 2004), well-defined mathematical objects are structured in nested hierarchies (decision trees) with each node representing a choice the player (DM) can make, each branch attached to a node representing an action, and each leaf following an action representing a payoff (Fudenberg & Tirole, 1991). As will be illustrated in the example to follow, a game-theoretic infrastructure can be constructed to model and test our normative model of DC. For a real-world example, imagine that you have been invited to two separate social gatherings on the same day in similar venues. Each has the same number of guests, but varies in the people attending. At both gatherings, there are people with whom you are not particularly fond of interacting. As an introvert, the thought of attending either event may prove stressful, but you have decided to at least talk to the person seated beside you at your assigned table. For simplicity's sake, we will assume there are four people at each gathering (each one at a separate table) with whom you are particularly averse to having to interact with. You predict the conversation will probably lead to adverse social interaction (e.g., a strong differing of opinions). These eight individuals could be ranked ordered from 1 to 8 (t_1, t_2, …, t_8; t representing threat of an adverse stress-inducing event; an act). There is a discernably increasing probability that a conversation will result in an adverse social event (t_8 being the highest probability, and t_1 being the lowest).

This example takes the form of a nesting-nested hierarchy in which the DM potentially engages one discrete (mutually exclusive) entity within a tier. The social gathering and the adverse interactions make up the architecture of our two-tier design (with parameters p and q; where p = the number of social gatherings = 2 and q = the number of eligible interactants within each = 4). This architecture is substantiated in Figure 1.

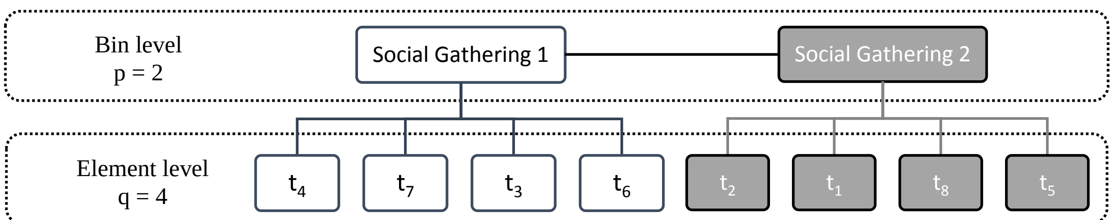

Figure 1. An example of a nesting-nested hierarchy (decision tree) with t_i elements randomized at the most subordinate level. Nodes are located along horizontal lines, with two at the bin level and four within each bin (eight total). In this example, t_i elements are illustrated as static, but would be randomly ordered each time the hierarchy is displayed. The two bin groups have been coloured differently for illustrative purposes; to make it easier to follow the nesting hierarchy.

As in life, control over which entity (node) is engaged is not always within the DM's control. DC can sometimes only be applied at certain tiers or not at all. In this model C is used to represent the scenario structure in which the DM has an unfettered choice (they have predictive information and decision-making power); *N* to represent external assignment with information but no decision-making power; and *U* to represent external assignment in which the DM has no information or decision-making power. To capture the essence of conditions *U* and *N*, their assignment is random from available options. In this way the elements are neither predictable or controllable for *U* or controllable for *N*.

Considering this two-tiered example (Figure 1), DC can succinctly be expressed in sentential logic. The definition of DC for a two-tiered hierarchy is

$$\exists\ J = \{x_1, x_2\} \ni \forall\ \mathrm{x_i} \in J,\ \mathrm{x_i} = C \veebar (U \veebar N), \qquad (1)$$

where $x_{1,2}$ denote the DC conditions for the upper and lower tiers, respectively (Neufeld, Shanahan, & Nguyen, 2014; Shanahan, Nguyen & Neufeld, manuscript in revision). Put simply, at each level of the two-tiered hierarchy, either a C, U, or N can be a presenting condition to be engaged by the DM. The total number of combinations form a set of *J*; in our example there are nine pairs, as ordered on the first and second tier (*CC*, *CN*, *CU*, *NC*, *NN*, *NU*, *UC*, *UN*, and *UU*). Any individual combination is further referred to as *j* in the set of *J*. Keeping with our example, in an instance of *CU*, the DM would be able to choose which party to attend but have no information about who is attending (the t_{i}'s nested within each party) nor any choice of which of the four people they will be required to sit beside. Alternatively, in *NC*, the DM will know which party they are attending (perhaps they were forced into attending one gathering by that gathering's hostess; information but no control in the gathering selection). In this scenario, however, they are told by the host the table at which each of the four people attending will be sat and the DM is given the choice of the table at which they would like to sit (information about which 4 individuals are attending and party-wise control).

In addition, each of the *pq* elements of the two-tiered hierarchy, has an unique appraised probability of adverse-event occurrence t_{i} (Shanahan & Neufeld, 2010) of

$$\{t_1 < t_2 < \ldots < t_{\mathrm{i}} < \ldots t_{\mathrm{pq}}\};\ \ t_{\mathrm{j}} < t_{\mathrm{i}} \text{ iff } j < \mathrm{i}\ ;\ t_{\mathrm{i}} \in [0,1]. \qquad (2)$$

As denoted in *Equation 2*, the threatened event is a Bernoulli outcome (either it happened/was encountered, 1, or not, 0) and *t* is the probability of its occurrence. In essence, and as stated in *Equation 2*, there are a number of possible levels of threat (i.e. t_1 through $t_{8,}$ with probability of engaging any t_{i} denoted $\Pr[t_{\mathrm{i}}]$) for the DM which get discernibly worse. As these discrete amounts are mutually exclusive and exhaustive, only one level of threat (e.g., a gauche interchange is the occurring outcome; t_i is the probability of its occurrence) will transpire and the probability of it occurring $Pr(t_i)$ is related to the level of expected threat, $E(t)$, expressed as

$$\sum_{i=1}^{pq} Pr(t_i)t_i \quad . \tag{3}$$

Each of these t_i values is randomly dispersed over the *pq* elements and can be engaged with different probabilities based on the conditions of control available to the DM. Assuming that stressor-event magnitude is such that those with higher t_i values are avoided to a greater extent (thus yielding lower probabilities), we can assume that when choice is given to the DM they will select options in favor of achieving the smallest t_i value available (referred to before as a maximizing or maximax strategy; Janis & Mann, 1977; Morrison, Neufeld, & Lefebvre, 1988; Rappaport, 1983). Given *CC*, it is assumed that the DM will always select t_1 upon making the appropriate number of cognitive appraisals required to discern the decisions necessary in reaching it. In our example, this requires only two operations of DC – to select the social gathering (bin) that contains t_1 and then select to sit at the table (element) with the individual representing t_1.

Using basic combinatorics, a potentially helpful way of visualizing the above engagement and probabilities is through a visual example using bin or urn terminology. Imagine transparent bins labelled t_1 through t_8, each containing an equal number of balls, some black and some white. The black balls represent an adverse event and the white balls represent a null event (a non-stressful event). If we say there are 8 balls in each bin, then the t_1 bin might have 1 black ball and 7 white balls and the t_8 bin might have 7 black balls and 1 white ball. These balls represent a Bernoulli outcome (there are only two possibilities), but the probabilities of drawing either a white ball or a black ball vary based on the bin. Further, the probability of accessing different bins varies based on the conditions of control (the choice-scenario architecture). The DM will attempt to always reach the t_1 bin (if available), as the probability that they will draw a black ball (encounter an adverse event) is minimal. In this way, the probability of drawing a black ball is nested within the probability of engaging a particular bin. If we relate this back to our example depicted in Figure 1: if you happen to find yourself in a *CU* condition, a maximizing/maximax strategy would dictate you would choose to engage in social gathering 2 in hopes of being assigned to table 1 (where the person represented by t_1 is present). If you happen to be assigned to table 5 (t_5) instead due to the uncertainty (*U*) at this level, it is still possible that your interchange with the person who you do not like at that table will not result in an unpleasant experience (i.e., experience a null event; although probabilistically you are more likely to experience an adverse event).

In scenarios where p and q are larger than in the above example (i.e. when there are more nested hierarchies, more elements within each, and a mixture of decisional-control conditions), there is a greater information processing demand on the DM (Shanahan, Pawluk, Hong, & Neufeld, 2012). This can be a source of stress in and of itself; one which must be balanced with the stress of the adverse events. This relationship is graphically represented in Figure 2.

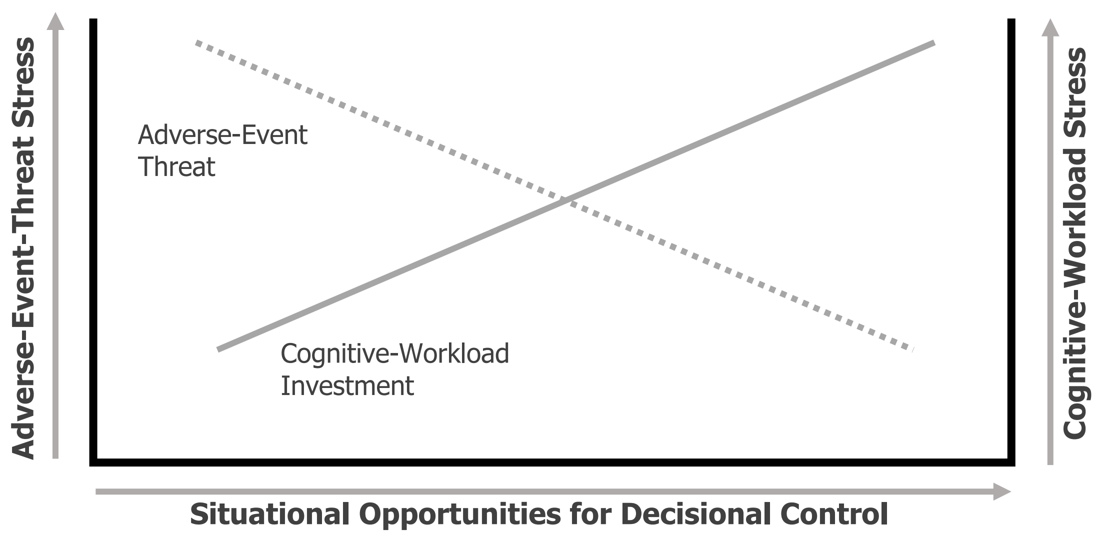

Figure 2. A simplified graphical representation of the hypothetical relationship between cognitive processing and the probability of experiencing an adverse-event.

As cognitive processing (and associated stress) increases, with increased potential outcome-set size, so does the probability of engaging the lowest-tier element (t_i). Alternatively, as cognitive processing is reduced (with the inclusion of more N conditions), the stress related to cognition decreases but the probability of engaging in a higher-tier element increases. This reciprocal relationship between predictive judgement investment (cognitive workload or “challenge”) stress and exogenous-event threat stress is what is known in decisional science as an “incompatibility of criteria” (Tversky, 1972a; Tversky, 1972b). Individual differences in coping strategies may be influenced by this dynamic interplay of sources of stress. Some individuals may prefer to adopt a maximizing/maximax strategy in order to make the “best decisions” in their pursuit of minimal t_i, whereas other’s may be willing to tolerate t_i values below t_5 (for example) if it requires less cognitive workload (weighing choices; an example of adopting a satisficing strategy). Different susceptibilities to one form of stress or the other, as they interface with prevailing DC conditions, represent person-environment fit examined here.

In defining a situation amenable to our above example, certain notation is used to specify the combination of *p* and *q* parameters (the number of elements at the first and second tiers of the DC architecture) and the pair of choice conditions from among *C*, *U*, and *N* that were present (one at each tier). Typically, the encounter is denoted “$Z_{\text{DC combination; pq}}$”, so in the example of *CU* we would report that this encounter took the form of $Z_{\text{CU; 2,4}}$. Let us revisit the *NC* example, but this time combine it with Figure 1. If we assume that the DM was forced into attending social gathering 1 by that event’s host (condition *N*, meaning an assigned element from the *p* elements composing the top tier, the assignment being disclosed at the outset). Next, they are made aware of the location of the four guests attending that could result in adverse social exchanges (and associated stress) and are able to choose which one to sit beside (*C*, meaning choice applied to the *q* elements of the lower tier). From Figure 1, we see that the DM can only choose from t_3, t_4, t_6, and t_7. We assume that they will likely choose t_3 as it is the act with the lowest probability for an adverse stressful encounter. If this scenario were run a few times, the number of times each t_i value was engaged would be reported as n_{ti}. Since *N* is randomly selected each time and there is a *p* of 2; one would expect that social gathering 1 and 2 would be assigned an equal amount of times. Since t_1 is eligible for selection at social gathering 2, one would predict, that if the scenario of $Z_{\text{NC; 2,4}}$ was run 10 times, that n_{t1}=5 and some combination of t_is other than t_1 = 5 (as the t_i are shuffled each encounter; unlike the static Figure 1). Thus we would expect the probability of engaging t_1 would be .50

($Pr(t_1) = 1/p$). In fact, all the probabilities for t_i can be readily computed for any two-tiered encounter using the formulas located in Appendix A (Neufeld, 1999; Shanahan, 2016; Shanahan & Neufeld, 2010). Some probabilities require combinatorics, based on whether t_1 is able to be engaged by the DM. Upon further investigation of each, we can see that certain combinations of conditional control are favorable to others (based on their probabilities of achieving t_1 and expectation of threat $E[t]$, which again entails $Pr[t_i]t_i$ from *Equation 3*). It is important to note that *C* must be present at one level in the scenario for DC to be available at all and that *U* at a subordinate level increases $E(t)$ significantly more than when it is positioned at the upper level (Shanahan et al., 2012; Shanahan & Neufeld, 2010). Putting all of these elements together, it should be self-evident that we have created a game-theoretic paradigm susceptible to testing. Each participant assumes the role of the DM, they are given differing levels of information and action at each node, and they are aware of (or learn) the differing payoffs (t_i values) related to each outcome. Unique to this DC normative model is the use of stochastic outcomes (Osborne & Rubinstein, 1994). By integrating stochastic outcomes, the environment has an active role in deciding the DM’s fate. This can be observed in conditions where control is not present, such as when a node is either an N or U condition. The environment either withholds information and choice or choice alone and assigns the DM a random action. We have a normative framework (the architecture) upon which we can test if participants conform to our predictions.

1.5 Mixture Modelling

By fitting choices to a quantitative framework, we can disentangle the interplay of different cognitive processes involved when judging environmental stressors. Through the individual differences people display in similarly defined situations, we create a normative model representing person-environment fit. Captured quantitatively, these differences can illustrate differential dispositions towards engaging in presented opportunities for choice (a descriptive model), which we can test against our normative model of predicted probabilities (afforded by our closed-form equational system). As coping strategies (and their underlying cognitive processes) are largely unique, individuals will vary in their task performance in situations amenable to DC. At the same time, in order to generalize our findings, we are interested in considering how well our model of DC performs with respect to a consensual, group-extracted, cognitive mapping. As such, three separate models are required; a normative model (based on conditions inherent in the environment), an individualized model (based on subjective appraisals of the environment), and a group model (based on the averaged subjective appraisals across the group).

One of the first requirements in setting up a mixture model is defining parameters. Parameter estimation normally requires random sampling from a particular conjugate (i.e. mathematically tractable) prior distribution that models the probability distribution of the parameters (i.e. rate or probability) we are looking for. One advantage of our particular setup is that we do not have to do this. We have our own discrete probabilities generated from the ground up by our DC architecture. The base-distribution parameters which pertain to the decision process itself are defined (t_i values) and are subject to a probability mixture, whose finite discrete probability mixing parameters are $Pr(t_i)$. We have already discussed the hyper-parameters above which help define the base-distribution; they are *C*, *U*, *N* and *p* and *q*. As we have already set up all of the architectures, including forming all our combinations (*j*) in our set (*J*) and their resultant probabilities (probability of base distribution parameter, $Pr(t_i)$). As such, we already have what we need to form multinomial likelihood functions involved in model testing. We are at an advantage having created a closed form solution, as we are able to generate every single discrete value. This can be likened to “samples” and “populations” in classical statistics. Typically, one samples from a population to generate a representative group upon which generalizations can be formed. In our case, we have the population of explicitly defined values and do not need to sample. In order to validate the model using quantitative predictions, engagements of particular t_i and their related stochastically distributed t_i, whose $Pr(t_i)$ values are governed by the prevailing structure (*j*), are used to create multinomial likelihoods.

1.6 Model Testing and Fit

The multinomial likelihood (ML) of n_{t_i} (the number of times each t_i value was engaged) is defined similarly to how an encounter ($Z_{\text{DC combination; pq}}$) was defined; $\text{ML}_{\text{DC combination; pq}}$ (in our previously discussed example for *CU* it would be illustratively represented by $\text{ML}_{\text{CU; 2,4}}$) and is represented by (Shanahan et al., manuscript in revision)

$$\frac{\left[Z_{C,\,U,\,N;\quad pq}\right]!}{\prod_{i=1}^{pq} n_{t_i}!} \cdot \prod_{i=1}^{pq} Pr\left(t_i\right)^{n_{t_i}} . \qquad (4)$$

In *Equation 4*, $Z_{\mathrm{C,U,N;\ pq}}$ is the total number of times a particular encounter was experienced, i.e. N_{ti} is the number of t_{i} engagements within that encounter, and $Pr(t_{\mathrm{i}})$ is the model stipulated probability of engaging a particular t_i within that encounter. Further, the prior probabilities of each of j combinations, π_{j}, within the J set of decisional structures can be represented by the combined multinomial likelihood (Shanahan et al., manuscript in revision)

$$\sum_{j=1}^{J} \pi_j ML_j . \qquad (5)$$

For the two-tiered DC structures, there are 9 unique combinations (j) possible within the set of J. These unique structures are made of *C*, *U*, and *N* at the bin level, factorially combined with *C*, *U* and *N* at the bin-element level (the J structure-combinations of j are mutually exclusive and exhaustive; the π_{j} sum to 1). Upon calculating a combined multinomial likelihood for each participant, we will have the necessary values of the descriptive model upon which to compare the theoretical predictions of our normative model. In short, we will compare our generated normative predictions to the descriptive, observed participant responding and determine how different element engagements (t_{i}) selectively conform to predictions from the prevailing j combinations (Shanahan et al., manuscript in revision). If we consider the prior case and apply our static *CU* example, we would expect our participants to always select social gathering 2 (in attempt to achieve t1). Due to the *U* nature of q, we would expect t_1, t_2, t_5, and t_8 to be engaged an equal number of times ($1/q = 1/4$).

When we speak about model fit in the present case, we are referring to how well the normative model-generated expected frequencies correspond to the actual observed frequencies of participants (the descriptive model). Here, we would want to see if participants, presented with a computer simulation representing the J combinations possible within our Figure 1 example, would show an almost identical pattern of n_{ti} as we would predict from our model assumptions. This equivalence is tested using the likelihood ratio chi-square statistic G^2. As no parameter estimates were necessary (due to our architecture, as mentioned above), both Akaike and Bayesian Information Criteria (which are both used to adjust G^2 based on the number of parameters being estimated) are not applied. As such, G^2 is simply equal to -2 *ln* multiplied by the likelihood ratio.

To estimate fit of the different descriptive models (Group model and Individualized model), we take the participant generated data and test its fit with our DC-tendered model's fit (Shanahan et al., 2012). To compute G^2, a generic saturated model is required to form the denominator of a likelihood ratio. In the latter case, the DC predictions are replaced with observed engagements; instead of the probability of t_i, the actual number of t_i engagements out of the total number of encounters are used. The generic descriptive model is used as a normalizing factor to create a G^2 value. This is illustrated as

$$\begin{aligned} G^2 &= -2\, ln \left(\frac{\text{Likelihood Function}_{\text{DC model}}}{\text{Likelihood Function}_{\text{generic saturated model}}}\right) \\ &= -2\, ln\ (\text{Likelihood Ratio}) \qquad (6) \\ &\approx \chi^2, \text{ when } n \text{ is large.} \end{aligned}$$

In contrast to our DC model used in the numerator, the generic, saturated model used in the denominator replaces model predictions with observed proportions of t_i selections (Riefer & Batchelder, 1988). Additionally, to compliment the G^2 value, a Pearson χ^2 value (Cohen, 1988, Chapter 7) will also be computed as the two converge with a large number of observations.

Based on results from a small simulation, the model of DC does perform as well as the generic saturated model (Shanahan et al., manuscript in revision). If our predictions and observations are close, we would expect a very good (low) G^2 and Pearson χ^2 value for our tendered models, indicating their ability to accurately predict empirical probabilities of responding. This serves as an estimate of model fit, whose sources of change and whose psychometric correlates are the subject of the current thesis.

In order to quantify and empirically test this environmental framework of DC and explore individual differences in responding, behavioral (e.g., choice selection and their latencies), psychophysiological (e.g., heart rate, skin conductance) and subjective measures (e.g., verbal reports, numerical ratings) of stress are collected. Past research has supported the use of these empirical measures quantifying DC composition (Shanahan & Neufeld, 2010). Gathered empirically, the complex interplay of the above indicators of stress can be disentangled to reveal differential dispositions in situational engagement and should conform to predictions of fluctuating levels of stress created by the environmental framework at both the group and individual level. However, the focus of the present thesis squarely is on sources of model fit. Other collected responses, including psychophysiological data, response times, and indices of stress generation will be analyzed in the future.

Psychometric measures selected to explore individual differences in sources of model fit include the Desirability of Control (DOC; Burger & Cooper, 1979), Need for Cognition (NFC; Cacioppo, Petty, & Kao 1982), Intolerance of Uncertainty (IOC; Freeston, Rheaume, Letart, Dugas, & Ladouceur, 1994) Uncertainty Tolerance Scale (UTS; Dalbert, 1996), the General Decision-Making Style questionnaire (GDMS; Scott & Bruce, 1995) and the Endler Multidimensional Anxiety Scale's Trait scale (EMAS-T; Endler, Parker, Bagby, & Cox, 1991). Selection of measures was informed by previous DC research or exploratory in nature. Elaboration of the measures is provided within the methods section.

1.7 Aim of Current Research

Thus, one aim of the present study is to implement a game-theoretic infrastructure upon which a probability mixture model can be built and tested using a normal population (undergraduate students). This infrastructure/environmental framework will allow the development of precise likelihoods of stress-relevant events and the ability to test the model at both an individual and group level (Shanahan et al., manuscript in revision). By implementing a self-contained model of DC, we can not only determine the probabilities of how individuals within a DC amenable scenario should respond (objective utility), but also use those computations to test our model (a combination of top-down and bottom up approaches to validation). Candidate sources of departure from the normative model (contingent/conditional-probability-based) predictions, notably departures in the form of individual and group cognitive mapping of t_i (subjective utilities) and decision-making strategies, can enter into comparisons with normative model prescribed values (objective utilities and maximizing/maximax selection strategy) and be correlated with psychometrics. This correlation encompasses the second aim of the present research. Doing so will allow for estimation of t_i values, to which the maximizing/maximax-strategy component of the normative model potentially applies, and also residual departure subsequent to allowing for individualized t_i estimation.

In summary, the intended purposes of this study are two-fold: a) to test the normative game-theoretic probability mixture model created for DC and b) to investigate sources of departure from the normative model including through the use of psychometrically profiling individual differences in DC “aptitude” (amenability).

The resultant model-based findings will provide empirical evidence that identifies previously untapped model-testing predictions, including choice-selection behavior and multinomial likelihood and Pearson χ^2 implementation of DC. If the DC normative model predictions align with empirical observations, the model could be adapted for use in future studies with clinical populations with known cognitive and decisional difficulties. This could allow theoretical and empirical exploration and interpretation of group differences in navigating stressful situations, which could increase our knowledge of aberrant or dysfunctional cognition leading to suboptimal, cognition dependant coping strategies in clinical populations.

Chapter 2: Methodology

2.1 Participants

Participants were recruited from Western University's undergraduate Psychology Research Participation Pool as partial fulfilment of course credit. Fifty-eight participants were recruited and tested. Twelve participants were removed as a result of a significant change in the paradigm (n = 8), a computer hard drive failing mid-experiment (n = 2), or a lack compliance to the task/poor motivation (n = 2). The final participant sample consisted of 20 males (Age M = 18.2, *S.D.* = 0.52, *Min* = 17, *Max* = 19, *Mode* = 18, and *Mdn* = 18) and 26 females (Age M = 18.7, *S.D.* = 1.25, *Min* = 17, *Max* = 21, *Mode* = 18, and *Mdn* = 18).

2.2 Inclusion Criteria

In order to participate in the present study, individuals needed to be under 30 years of age, right-handed, and self-reported good English reading comprehension. Age is positively correlated with diminished electrodermal activity (Boucsein, 2006), with noticeable age-related skin changes posited to influence electrodermal activity beginning at 30 years of age (Boucsein, 2006). The criteria for age was due to this phenomena, as psychophysiological data was collected for future analysis and not as part of the present thesis.

2.3 Exclusion Criteria

The presence of a self-reported hearing problem is this study's only exclusion criteria.

2.4 Apparatus

Equipment used for data collection consisted of three separate hardware platforms, one for cognitive, psychometric, and psychophysiological collection.

2.4.1 Cognitive research platform.

Cognitive data collection occurred on an internet-disabled desktop computer with Windows 7 operating system. The participant and computer were in a room separated from the experimenter by a one-way mirror. The participant was positioned so the experimenter could observe the participant's behavior, including the participant's attention to the task, any discomfort with the adverse noise, choice selections, and time spent on instructions. A bell located on the participant's desk was used to signal task completion or request assistance. Presentation of stimuli and collection of behavioral responses were completed on the computer using behavioral experiment software (E-Prime 2.0). Additional responding related to the learning paradigm was collected on paper forms.

2.4.2 Psychometric research platform.

The Measures phase occurred in the data collection area of the research laboratory using an internet-enabled Gateway laptop running Windows 7. Paper-based questionnaires were transferred to an online survey software platform (Qualtrics ™), and this software was used to administer questionnaires electronically.

2.4.3 Psychophysiological apparatus.

Psychophysiological data was collected using equipment manufactured by Biopac (BIOPAC Systems, Inc., Goleta, CA). The MP-150 Data Acquisition System, in conjunction with ECG-100C (electrocardiography) and EDA-100C (electrodermal activity) modules, were used to collect heart rate and electrodermal activity. Heart rate was measured using two adhesive, disposable, snap Ag/AgCl electrodes in a Lead II configuration, one on the carotid artery above the right collarbone and the second located medial above the left ankle. This Lead II configuration was incorporated to avoid impeding responses and to decrease movement artifacts associated with the participants making selections with their right hand. Electrodermal activity was measured using two electrodes on the participant's left hand, one on each on the first phalanges of the index and middle finger (i.e., fingertips). The software package AcqKnowledge 4.1 was used to record the signals associated with these electrodes and perform computations. Logitech stereo desktop speakers were used to generate white noise at a controlled decibel level (85 dB) for the informed consent sample and during the Learning and Testing phases.

2.5 Measures

Published measures exploring a variety of personality and dispositional characteristics of participants were recreated digitally on an online survey software platform (Qualtrics ™) and administered to participants using a laptop computer. The measures selected explore concepts relevant to DC, including desire for control or cognition, intolerance of uncertainty, decision-making style, and features of trait anxiety.

In addition, following probability learning trials (described below), a probability rating sheet and a rank ordering sheet were used to measure a participant's judgement of the probability and the ordinal ranking that a particular letter would be followed by an adverse noise respectively. These sheets were administered after each trial in the Learning phase and at the conclusion of the Testing phase of the overall procedure.

2.5.1 Desirability of Control.

The Desirability of Control scale (DOC; Burger & Cooper, 1979) was developed to assess motivation to control of events in one's life. It is a 20 item measure that uses a seven-point Likert scale (1 = *The statement does not apply to me at all;* 7 = *The statement always applies to me)*. A factor analysis conducted by Burger and Cooper (1979) found five factors accounting for 50.4% of DOC variance: General Desire for Control (e.g., "I enjoy having control over my own destiny"); Decisiveness (e.g., "There are many situations in which I would prefer only one choice rather than having to make a decision"); Preparation-Prevention Control (e.g., "I like to get a good idea of what a job is all about before I begin"); Avoidance of Dependence (e.g., "I try to avoid situations where someone else tells me what to do"); and Leadership (e.g., "I would rather someone else take over the leadership role when I'm involved in a group project"). The DOC scale demonstrates good reliability and validity, with adequate construct validity and good test-retest reliability (α =.78 and α =.76) according to McCutcheon (2000) and has been used in previous DC research (Shanahan, 2016).

2.5.2 Need for Cognition.

The Need for Cognition scale (NFC; Cacioppo, Petty, & Kao 1984; Cacioppo & Petty, 1982) was developed to assess the tendency and enjoyment in using information processing when presented with activities amenable to its use. The 34-item Likert scale has nine anchors (-4 = *very strong disagreement;* 4 = *very strong agreement*). The NFC has strong internal consistency (α =.90; Cacioppo et al., 1984) and measures a single factor. Sample questions include "Thinking is not my idea of fun" (reverse scored) and "I really enjoy a task that involves coming up with new solutions to problems". The NFC has been applied successfully in previous DC research to psychometrically profile participants (Shanahan, 2016) and abdicate an ability-dependant view of DC in favor of a personality-dependant view (Benn, 2001, 1995).

2.5.3 Intolerance of Uncertainty Scale.

The Intolerance of Uncertainty Scale (IUS; Freeston, Rheaume, Letarte, Dugas, & Ladouceur, 1994) is a 27-item measure initially constructed to evaluate emotional, cognitive, and behavioral reactions to uncertainties implicit in situations, oneself, and the future, as well as the resulting implications of uncertainty on the individual. Items such as "It frustrates me not having all the information I need" and "I must get away from all uncertain situations" are rated using a five-point Likert scale (1 = *not at all characteristic of me*; 5= *entirely characteristic of me*). While the scale is scored using a single summary score, a recent review of factor analytical studies has noted a variety of underlying factors measured by the IUS (Birrell, Meares, Wilkinson, & Freeston, 2011). In their review, Birrell and colleagues (2011) identified two consistent factors tapped by the IUS including the "desire for predictability and an active engagement in seeking certainty" (IUSF1) and the "paralysis of cognition and action in the face of uncertainty" (IUSF2). The IUS has been successfully used in recent DC research (Shanahan, 2016), correlating significantly with measures related to DC and possessing a Cronbach's alpha of 0.91.

2.5.4 Uncertainty Tolerance Scale.

The Uncertainty Tolerance Scale (UTS; Dalbert, 1996, 1999) measures the tendency to evaluate uncertain situations as a challenge or as a threat. Responses to the eight items fall along a 6-point Likert-scale (1 = *strongly agree*; 6 = *strongly disagree*. Sample items include "I like unexpected surprise" and "I like to let things happen". The scale has been used successfully in a number of studies by its creator (Dalbert, 1999, 1996a, 1996b; Otto & Dalbert, 2011) and others (Bardi, Guerra, & Ramdeny, 2009; Bude & Lantermann, 2006).

2.5.5 General Decision-Making Style.

The General Decision-Making Style (GDMS; Scott & Bruce, 1995) questionnaire is a 25-item measure with five scales comprised of five questions each. Each scale refers to conceptually independent, but not mutually exclusive, decision-making styles. They are: Rational, Intuitive, Dependant, Spontaneous, and Avoidant (GDMS-R, -I, -D, -S, and -A respectively). Scott and Bruce (1995) found that their results supported individuals adopting a combination of decision-making styles when making important decisions and reported internal consistency values (Cronbach's alpha) for each style ranging from .68 to .94. Items are endorsed along a five-point Likert scale (1 = *strongly disagree; 5= strongly agree*) and include the following sample items: "My decision making requires careful thought" (Rational), "When making decisions, I rely upon my instincts" (Intuitive), "I rarely make decisions without consulting other people" (Dependent), "I postpone decision making whenever possible" (Avoidant), and "I generally make snap decisions" (Spontaneous). One item reported missing by Appelt, Milch, Handgraaf, and Weber (2011) from the original publication for the Rational scale was absent in our conducted research as well. The 24-item GDMS has been used effectively in the past to psychometrically profile participants (Shanahan, 2016).

2.5.6 Endler Multidimensional Anxiety Scale – Trait scale.

The Trait scale of the Endler Multidimensional Anxiety Scale (EMAS-T; Endler, Parker, Bagby, & Cox, 1991) is used to measure several facets of trait anxiety. It does so along four situational dimensions: Physical Danger, Social Evaluation, Novel Situations, and Daily Routine (EMAS-PD, -SE, -NS, and -DR respectively). Each dimension describes a situation pertinent to what it is measuring and poses 15 identical statements regarding the responder's reactions and feelings. These statements are endorsed along an intensity scale ranging from 1 (*Not at all*) to 5 (*Very much*) and sample statements include "Seek experiences like this" (reverse scored), "Feel upset", "Perspire", and "Heart beats faster". Coefficient alpha reliabilities reported by Endler et al. (1991) for a Canadian undergraduate population on all subscales of the Trait scale are over .92 for both men and women. The EMAS-T has been used successfully in past DC research to psychometrically profile individual dispositions linked to its application (Benn 2001; Shanahan, 2016).

2.5.7 Probability Rating sheet.

The probability rating sheet was modelled after one used by Lees and Neufeld (1999) and consisted of a column of ten blank spaces to write a letter and adjacent 100 mm lines. Each 100 mm line was marked with an anchor at 0, 25, 50, 75, and 100 percent. The sheet is used by participants to demark the probability they believe a particular learned letter will be followed by a stressor.

2.5.8 Rank Ordering sheet.

The rank ordering sheet consisted of 10 blank spaces anchored on the left with the word "lowest" and on the right with "highest". A randomized ordering of the 10 letters participants would learn to associate with a stressor adorned at the top. Participants were instructed to fill in the 10 blank spaces with the letters in an ordering they believed went from the lowest to highest probability of being followed by a noise (the stressor).

2.6 Procedure

The experiment consisted of four separate phases hereafter referred to as the Measures, Learning, Practice, and Testing phases (elaborated upon below). Learning and testing phases were modelled after the general procedures outlined in Kukde and Neufeld (1994) and Morrison et al. (1988). Prospective participants read and discussed a brief description of the experiment with the experimenter and were exposed to a one-second burst of 85 dB white noise from the computer speakers prior to obtaining informed consent. All participants agreed to continue and none withdrew.

2.6.1 Measures phase.

During the measures phase, participants completed the digitized measures (i.e. the DOC, NFC, UTS, EMAS, IUS, and GDMS) using Qualtrics™ software on a laptop computer in the recording area of the laboratory. A research assistant was present to answer questions and clarify wording for participants. The measures phase took approximately 30 minutes to complete.

2.6.2 Learning phase.

Following the Measures phase, participants were led to the recording area of the laboratory, where they sat at a desk with a computer and keyboard. Participants were presented with three rounds of learning trials, each followed by a probability judgement trial. All instructions were presented on the computer screen and participant feedback during the probability judgement trials was elicited through the use of the probability rating sheet and ranked order sheet.

Each learning trial consisted of the same 104 presentations of capital, English alphabetic letters paired with either an "innocuous event" or a "stressor". Each innocuous event was a one-second computer screen presentation of a green screen (a non-significant event) and each stressor was a one second burst of 85 dB white noise from the computer speakers. The stressing properties of the stressor have been ascertained according to Thurstonian and other scaled subjective and psychophysiological responses in previous DC research and related studies (Kukde & Neufeld, 1994; Lefave & Neufeld, 1980; Neufeld & Herzog, 1983; Neufeld & Davidson, 1974). The 104 letter-outcome pairs and the conditional probabilities of a stressor given a letter are both included in Table 1. For an example of a conditional probability, the letter D would appear seven times per trial, two times with a green screen (innocuous event) and five times followed by the white noise stressor (giving a conditional probability of 5/7=0.71%). Ordering of these letter-outcome pairs was randomized across participants and between trials; all participants received the same pairs, but in completely random order. The ten letters selected were identical to those used in Kukde and Neufeld (1994) and Morrison et al. (1988). Their selection was such that the probability of misidentifying one letter for another was less than 0.10, as indicated by Townsend's (1971) confusion matrix. The paradigm used in this study and the above mentioned studies is one pioneered by Estes (1976). Estes' paradigm allows differential anticipatory stress to occur in response to the chosen letters due to memory association mechanisms of probability learning (cf. Estes 1976). Unequal letter frequencies are such that stressor and innocuous events are uncorrelated (r =.02), but still amenable to Estes' (1976) model of "categorical memory". In essence, Estes' paradigm is designed such that each letter possesses its own inherent probability of a stressor and is implicitly separate from the probabilities of other letters. Past research has evidenced that participants' judgement rankings have a greater tendency to align with the frequency of stressor occurrences than the conditional probabilities (Morrison et al.,1988; Mothersill & Neufeld, 1985; Neufeld & Herzog, 1983). As such, the reported subjective probabilities from participants in past studies (Lees & Neufeld, 1999; Morrison et al., 1988) were averaged with the conditional probability to create a hybridized probability. This hybridized probability is given in Table 1 as the probability of stressor occurrence during the Experiment phase. It dictates the probability of feedback during the Testing phase to better align with participant expectations of stressor/innocuous event probability.

Table 1

Letters for Stimulus Presentation (During Learning and Testing phases) and Associated Frequencies and Probabilities

Letter stimulus	D	B	J	L	M	A	Z	V	P	G
Letter frequency	7	12	9	5	9	6	14	11	18	13
Relative frequency of stressor	5	4	1	2	2	4	6	7	8	9
Relative frequency of innocuous event	2	8	8	3	7	2	8	4	10	4
Conditional probability of stressor given letter occurrence	0.71	0.33	0.11	0.40	0.22	0.67	0.42	0.64	0.44	0.69
Probability of stressor occurrence during Testing phase	0.61	0.42	0.21	0.41	0.33	0.62	0.50	0.63	0.48	0.69

During each learning trial, a letter appeared on the computer screen for two seconds followed by a two-second delay and then a one-second innocuous or stressor event. A three-second inter-trial interval would precede the subsequent letter presentation to allow psychophysiological responding to return to baseline. Participants were instructed to say aloud any letter paired with a stressor by saying the letter and the word "noise". For example, if the letter Z was presented and followed by the stressor, a participant would say "Z noise". If a letter was not followed by a stressor, they were instructed to say nothing. This methodology was adopted to facilitate the encoding of letter-outcome pairs from a modified Estes' (1976) paradigm found to produce the greatest salience to noise frequency by Neufeld and Herzog (1983) and to enhance traces in categorical memory on which probability judgements were found to be determined (Estes, 1976).

To lessen the cognitive demands of the task on memory and enhance learning, participants were instructed to arrange ten physical blocks, each with a letter written on it, in order from least to most likely to be followed by a stressor during inter-trial intervals. Participants were requested to continue to order the blocks within and across all three learning trials. Participants were informed that all learning trials contained the same frequency of letter-outcome pairs with only the ordering randomized.

Participants completed a probability judgement trial following each learning trial. During a judgement trial, participants were presented with a random letter on screen for two seconds and given a six-second window to record on the Probability Rating sheet the letter presented and demark on the line the probability of the letter being followed by the stressor. Judgements were requested under a short timeframe of six seconds to encourage participants to report their initial beliefs and not deliberate their answers. Participants then completed a ranked ordering of the letters from least to most likely to be followed by a stressor on the Rank Ordering sheet. Once all answers were recorded, participants were given a two-minute break before the subsequent learning trial began. The Learning phase took approximately 45 minutes to complete.

2.6.3 Practice phase.

Following the Learning phase, participants were instructed on the rules of a DC framework and practiced making selections as they would in the Experimental phase. Participants were given a sheet containing a separate set of ten letters and their hypothetical probability of being followed by a stressor. They were instructed to make selections using these letters for the preliminary Practice phase and informed that the ten letters they had previously learned to associate with stressor occurrences would be present in the Testing phase. No stressor occurrences were provided during the Practice phase trials and feedback was displayed for both correct and incorrect selections to enhance rule learning. Electrodes and leads were connected at the beginning of this phase to allow time to adhere and calibrate. Participants were encouraged to ask questions to the experimenter if any anything was confusing or needed clarification. The Practice phase took approximately 15 minutes to complete.

2.6.4 Testing phase.

Participants were instructed to respond as they saw fit while obeying the rules of the paradigm. They were also requested to make responses as quickly and accurately as possible and reminded that the letters they had learned before would be presented and followed by either a stressor or an innocuous event. They were informed that although good performance on the task would result in a reduced probability of experiencing the stressor, it would not altogether eliminate its occurrence.

All nine architectures (*j*) were presented twelve times within a block. Participants completed three blocks in total with a break of unspecified length (participant's choice) between each block. Architectures were presented in randomized order with each trial including a randomized selection of eight of the ten possible letters. An example of each architecture, as they would be presented to participants, and how participants should respond can be found in Appendix J.

At the beginning of each trial, participants were instructed to relax for three seconds. Following the "relax" screen, they were instructed to depress the space bar which would display the architecture and elements until they were ready to make a selection. Upon deciding which element to select (from subjective preference and in accordance with the rules of the game theoretic paradigm) they would release the space bar and type the letter on the keyboard. Depression of the space bar followed by a selection is a method used to collect decision-time estimates, a behavioral measure to be combined with psychophysiological activation for future consideration. Two seconds after their selection they would receive either an innocuous or stressor outcome for one second dependant on the probability of stressor occurrence during Testing phase in Table 1 (in an effort to maintain credibility of the experimental treatments). After a half second delay, they would proceed to the next trials relax screen. Following four presentations of each architecture per block, however, participants would instead be directed to a stress measurement scale before going to the next trial. The stress measurement scale would ask how stressed they were during the past trial from one (no stress) to five (a lot of stress). Each experimental block took approximately 30 minutes to complete.

After the last experimental block, participants completed a final Probability Rating sheet and Rank Ordering sheet. They then received a debriefing sheet and were assigned course credits for their participation depending on the length of time spent completing the experiment (.5 credit per half an hour up to 4 credits maximum).

Chapter 3: Results

The results section is broken up in two main parts with several subheadings. The results begin by addressing the primary goal of the current research, testing the DC model. These results are followed by descriptive statistics of the psychometric measures and their correlations with model testing with the aim of psychometrically profiling DC amenability.

3.1 DC Model Testing

3.1.1 Indication that learning occurred and participant removal.

Bivariate correlations were completed to investigate the relationship between the group-averaged subjective probability ratings pre- and post-Testing phase and the components of Table 1. Significant correlations in order of increasing Pearson's correlation coefficients were found between the relative frequency of stressor ($r(8) = .89$, $p = .001$); the conditional probability of stressor given letter occurrence ($r(8) = .93$, $p < .001$); and the probability of stressor occurrence during Testing phase ($r(8) = .97$, $p < .001$). Group-averaged subjective probability ratings were not significantly correlated with the relative frequency of the innocuous event ($r(8) = -.42$, $p = .23$).

Additionally, bivariate correlations were calculated between the group-averaged subjective probability ratings pre- and post-Testing phase and the subjective probabilities of two past DC studies using the same Estes' (1976) learning paradigm. This was done in an effort to investigate if our participant sample had learned the probabilities and mapped the t_i values in a corresponding way to past research conducted. Pearson's correlation coefficients between both participant's ratings in Morrison et al. (1988) and Lees and Neufeld (1999) were highly significant, $r(8) = .92$, $p < .001$ and $r(6) = .96$, $p < .001$ respectively. With these strong correlations, we can say that the findings are consistent with past research utilizing the same learning paradigm. Also supported is the use of these past studies subjective probabilities in creating a hybridized probability used in the Testing phase (see the Methods section for more details).

As an indication of participants sufficiently learning and retaining letter probabilities during the Learning phase, scores on probability rating sheets pre- and post-

Testing phase were investigated. Spearman's rank correlations (rho) were calculated between participant subjective probability ratings pre- and post-experiment, as the ratings become monotonically related ranks (t_i values). Spearman's rank correlations were used as an indicator of consistent learning, and, if participants' pre- and post-experiment scores did not correlate highly, it was attributed to a reappraisal of the probabilities (subjective utilities) within the experiment. As choice selection is assumed to be dependant on consistent use of MAX EU, a large change in SEU during the Testing phase undermines the model and our tests of fit. For a participant to be evaluated under this model, it must be insured that the only departures from the model are due to fit between objective utilities and subjective utilities and the decision-making strategy chosen. If participants do not learn the ordering of subjective utilities, we can not attribute the departure from the model as either specified source. Participants with a rank correlation above .60, indicative of a strong or very strong correlation (Evans, 1996), were kept for further analyses. This criterion removed ten participants, bringing the remaining number of participants to 36. This group of participants will hereafter be referred to as the Learners Group, as they showed a high level of consistent learning and ordering of subjective utilities. The group with all participants (except for the 12 eliminated on grounds mentioned in the Methods section) will be referred to as the All Group (n = 46).

3.1.2 Data cleaning procedures.

Participant data was investigated for any inconsistent rule following during the Testing phase. Trial data found inconsistent of the rules was removed from analysis or recoded. If the correct answer could be inferred (through the lack of choice, e.g., in an NN scenario) or was randomly distributed at the subordinate level (e.g., NU) data was recoded. In instances where a selection was outside of the available choices (not displayed as an option) and choice selection could not be inferred (e.g., NC), data was removed from the total counts for that particular structure (j). Descriptive statistics for the frequencies are as follows: for the All Group, removed data (N = 46, M = 5.04, SD = 7.57, Mdn = 1.5, Min. = 0, Max. = 26, Range = 26) and recoded data (N = 46, M = 14.28, SD = 10.37, Mdn = 12.5, Min. = 1, Max. = 38, Range = 37); and for the Learners Group, removed data (N = 36, M = 5.36, SD = 8.06, Mdn = 1.5, Min. = 0, Max. = 26, Range =

26) and recoded data (N = 36, M = 13.28, SD = 10.63, Mdn = 8, Min. = 1, Max. = 38, Range = 37).

3.1.3 Subjective utilities of t_i values.

Three models of possible fit were conducted to explore fit with our normative model; each varying the tendered utilities for each t_i value.

The first model, hereafter referred to as the Conditional model, assumed participants' subjective utilities were in alignment with the conditional probabilities of stressor (given letter occurrence) found in Table 1. This model is viewed as the one containing the objective utilities upon which a normative model would prescribe choices be made.

The second model, hereafter referred to as the Group model, averaged all participants' subjective probability ratings pre- and post-Testing phase and created a group mean of these means. In essence, the Group model contains the group consensus on the subjective utilities of each t_i value and individual participants' utilities were compared to that using the group subjective utilities.

The last model, hereafter referred to as the Individualized model, investigated model fit using each individuals' subjective utilities. Using the average of their pre- and post-Testing phase probability ratings, t_i values were constructed for each participant. In instances where one or more t_i values were tied, averaged rank orders from the Rank Ordering sheet were used to break the tie. In one rare case where both the averaged probabilities and rank orders were tied, the tie was broken using the participants second Probability Rating sheet (that occurred before the pre-Testing phase).

Table 2 displays the t_i rankings for both the Conditional and Group model.

Table 2

Conditional and Group Rank Orderings and Probabilities of Letter Presentations

Rank of t_i	1	2	3	4	5	6	7	8	9	10
Conditional model letter rankings	J	M	B	L	Z	P	V	A	G	D
Conditional model objective probabilities of stressor given letter occurrence	0.11	0.22	0.33	0.40	0.42	0.44	0.64	0.67	0.69	0.71
Group model letter rankings	J	M	L	B	Z	P	A	D	V	G
Group model subjective probabilities of stressor given letter occurrence	0.16	0.23	0.33	0.35	0.51	0.55	0.57	0.60	0.66	0.69

3.1.4 G^2 and Pearson χ^2 calculations.

As specified in the introduction, DC model and generic saturated model multinomial likelihoods were calculated for each particular structure (j) using participant selections and t_i rankings (above). Values were calculated for each of the nine structures using these likelihoods and a summed aggregate (per participant) was created for each model. This aggregate value represented the overall fit between the participant's empirical responses and the model predictions.

3.1.5 Outliers, normality, and transformation.

Outlier data was screened using methodology recommended originally by Tukey (1977) and updated by Hoaglin and Iglewicz (1987). This stringent form of outlier removal multiplies the difference between the 25th and the 75th percentile by a factor of 2.2. This product is then added to the 75th percentile and removed from the 25th percentile, with extreme values falling outside of this range. Using this methodology, one G^2 value and three Pearson χ^2 values were removed. Due to the listwise nature of repeated measures ANOVA, the final participant count used in the ANOVA analysis below was 32.

The assumption of normality was tested through examination of the unstandardized residuals for all G^2 and Pearson χ^2 values. Review of the Kolmogorov-Smirnov (Lilliefors correction) and the Shapiro-Wilk tests of skewness and normality suggested both were violated and histograms suggested data was positively skewed in all cases. For G^2, $D(32) = .19$, $p = .005$ and $W(32) = .86$, $p = .001$, $D(32) = .20$, $p = .002$ and $W(32) = .84$, $p < .001$, and $D(32) =.20$, $p = .002$ and $W(32) = .89$, $p = .003$ for the Conditional, Group, and Individualized models respectively. For Pearson χ^2, $D(32) = .25$, $p < .001$ and $W(32) = .76$, $p < .001$, $D(32) = .24$, $p < .001$ and $W(32) = .77$, $p < .001$, and $D(32) = .22$, $p < .001$ and $W(32) = .77$, $p < .001$ for the Conditional, Group, and Individualized models respectively.

Due to violations in normality, a log10 transformation was performed on the data (Field, 2013). Following the transformation, no significant violations of normality were observed and no outliers were recommended for removal. As results from analyses performed below were in alignment with results occurring with the log10 transformed data, results on untransformed data alone are presented in both the ANOVA and correlations.

3.1.6 Repeated measures one-way ANOVA.

A one-way within subjects (repeated measures) ANOVA was conducted to compare the effect of model (Conditional, Group, and Individualized) on G^2 and Pearson χ^2 fit indices. Mauchly's test indicated that the assumption of sphericity had been violated for the main effects of model on both G^2 and Pearson χ^2 values, $\chi^2(2) = 18.43$, $p < .001$ and $\chi^2(2) = 52.23$, $p < .001$ respectively, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon = .69$ and $\varepsilon = .55$ respectively). The results show that the G^2 and Pearson χ^2 values were both significantly affected by which t_i configuration that was used, $F(1.37, 42.50) = 12.02$, $p < .001$, $\eta_p^2 = .28$ and $F(1.10, 33.98) = 8.77$, $p = .005$, $\eta_p^2 = .22$ respectively.

A priori post hoc tests using the Bonferroni correction were conducted and were appropriately warranted given the statistically significant omnibus ANOVA F-test. All significance testing reported below used two-tails in order to be conservative. For G^2

values, no significant difference was found between the Conditional (*M* = 192.14, *SD* = 117.25) and Group model (*M* = 172.00, *SD* = 106.25), however, there was a significant difference between the Individualized model (*M* = 116.59, *SD* = 60.19) and both the Conditional model (p = .002, Cohen's d_z = .70) and the Group model (p = .006, Cohen's d_z = .60). For Pearson χ^2 values, the same pattern appeared with no significant difference between the Conditional (*M* = 705.55, *SD* = 783.48) and Group model (*M* = 733.10, *SD* = 832.51), but a significant difference between the Individualized model (*M* = 288.20, *SD* = 294.79) and both the Conditional model (p = .018, Cohen's d_z = .52) and the Group model (p = .014, Cohen's d_z = .54). Estimated marginal means patterns are depicted in Figure 3 and Figure 4.

3.1.7 Canonical correlations.

In addition to the repeated measures analysis, a canonical correlation analysis was conducted in order to determine the relationship between the three G^2 values and the three Pearson χ^2 values. The first of the two variable sets consisted of the three G^2 values and the second set consisted of the three Pearson χ^2 values. Two separate canonical correlations were conducted, one with all participants (the All Group) and the other with the Learners Group. The results presented below are for the Learners Group; All Group results can be found in Appendix B. Bivariate Pearson correlation coefficients between the fit indices can be found below in the Correlations section of Psychometric Data.

Results from the Learners Group indicated three significant canonical functions emerged, R_c = .974, Wilk's Λ = .006, $F(9, 73.16) = 56.32$, p < .001, for function 1; R_c = .885, Wilk's Λ = .127, $F(4, 62.00) = 27.952$, $p < .001$, for function 2; and R_c = .643, Wilk's Λ = .587, $F(1, 32.00) = 22.56$, $p < .001$, for function 3. As Wilk's Λ represents the variance unexplained by the model and 1- Λ gives us the full model effect size in r^2, the full model explained about 99.4% of the variance shared between the two variable sets. Given that the R_c^2 effects for the first two functions accounted for 95% and 78% of shared variance respectively, only the first two functions were considered relevant in the context of the study.

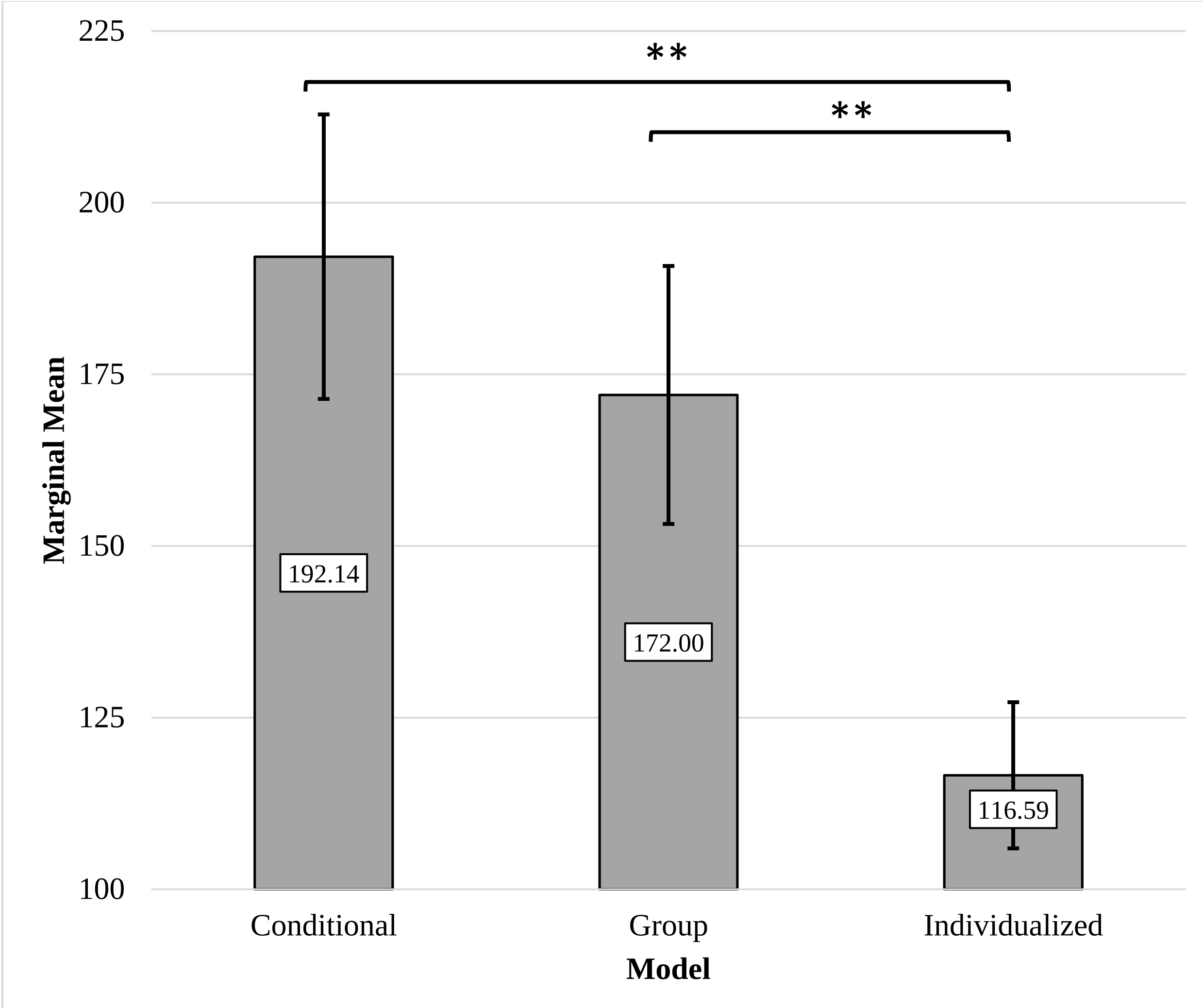

Figure 3. Marginal Means of G^2 Values for the Three Models. Error bars represent standard error of the marginal means. * indicates p <.05; ** indicates p <.01.

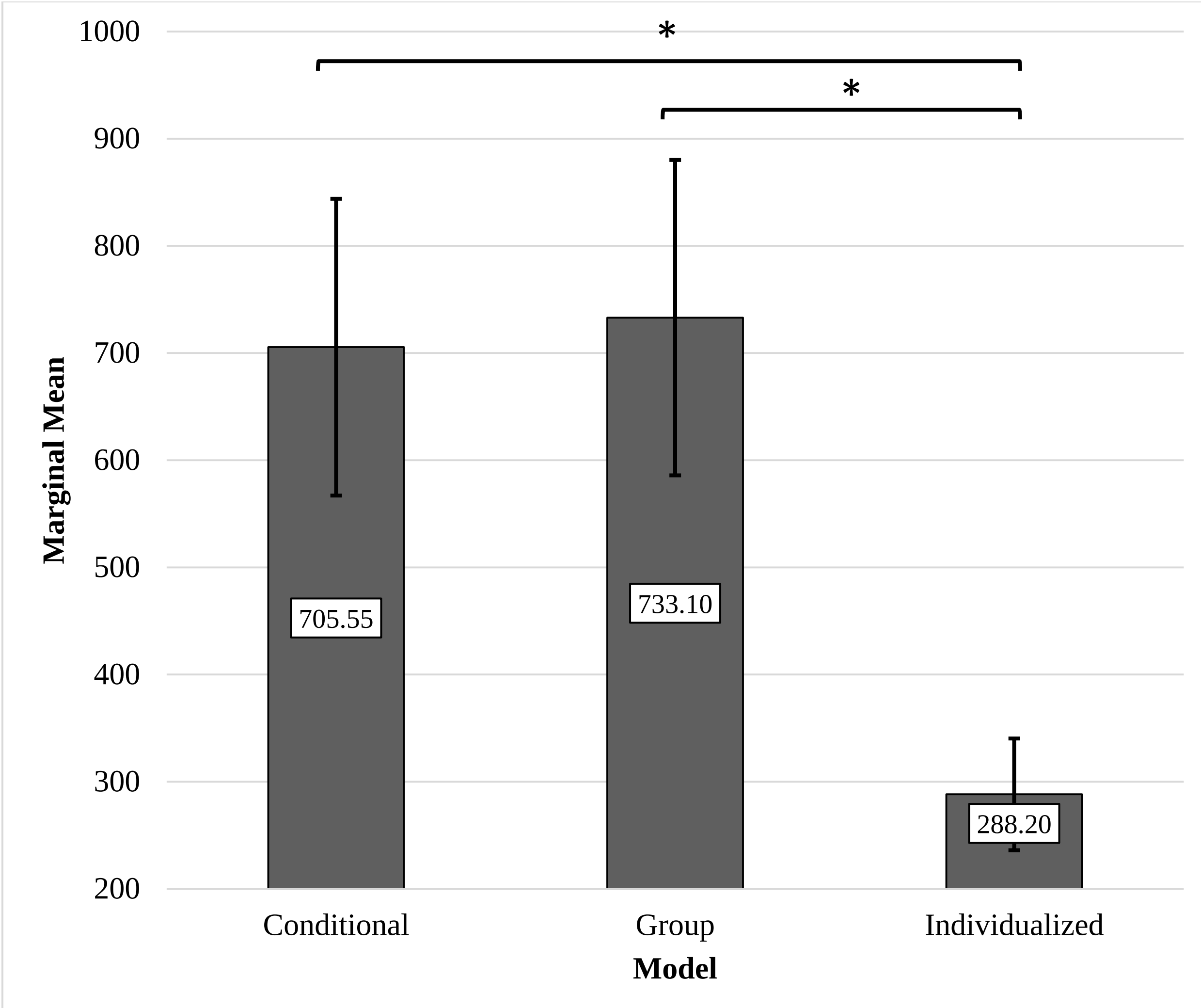

Figure 4. Marginal Means of χ^2 Values for the Three Models. Error bars represent standard error of the marginal means. * indicates *p* <.05; ** indicates *p* <.01.

In the first function, all of the G^2 values of the first set (Individualized Model [-.649], Group Model [.557], and Conditional Model [.509]) and all of the Pearson χ^2 values of the second set (Individualized Model [-.716], Group Model [.686], and Conditional Model [.656]) loaded onto the function with moderate canonical loadings. The redundancy indices for the first and second set were .341 and .447 respectively. Of particular interest is the directionality of the two Individualized Model fit values which are negatively related to this canonical variate relative to the other two models. As participants' subjective utilities of rank t_i values dominate their t_i selections, their fit values on the Group and Conditional models become worse and vice versa. It appears that the first factor is parsing out two sets of individuals, those who rely on subjective utilities and those who rely on environmentally defined utilities. Elaborately separating those whose cognitive mapping was rooted in uniquely subjective utilities, which surmounted normative and group choice selection, and those who correctly inferred the environment defined utilities and whose subjective utilities evidently corresponded to normative utilities.

In the second function, all of the G^2 values of the first set (Individualized Model [-.758], Group Model [-.829], and Conditional Model [-.477]) and all of the Pearson χ^2 values of the second set (Individualized Model [-.698], Group Model [-.727], and Conditional Model [-.685]) loaded onto the function with moderate to high canonical loadings. The redundancy indices for the first and second set were .389 and .387 respectively. From these results, there appears to be a factor which accounts for unidirectional variance in each model which is not accounted for by the first factor.

3.2 Psychometric Data

A MANOVA was run to investigate any gender differences in psychometric responding and with fit indexes prior to reporting descriptive statistics. No significant results were found and descriptive statistics reported below will be collapsed across gender.

3.2.1 Desirability of Control.

The DOC with college students has a theoretical mean around 100 and a standard deviation around 10. Participant scores on the DOC were normally distributed (n = 36, M = 99.14, SD = 8.19, and range = 83 to 115).

3.2.2 Need for Cognition.

The need for cognition has a theoretical range from -136 to 136. Participant scores on the NFC were normally distributed (n = 36, M = -5.11, SD = 15.43, and range = -42 to 28). A positive score represents an enjoyment in using cognition and a negative score represents an aversion to it.

3.2.3 Intolerance of Uncertainty.

The need for cognition has a theoretical range from 27 to 135. Participant total scores on the IUS were normally distributed (n = 36, M = 65.89, SD = 13.51, and range = 38 to 98), as were the aggregated scores on the two factors identified by Birrell et al. (2011) as "desire for predictability and an active engagement in seeking certainty" (n = 36, M = 34.67, SD = 8.28, and range = 17 to 51) and "paralysis of cognition and action in the face of uncertainty" (n = 36, M = 21.19, SD = 4.79, and range = 12 to 29). Hereafter, the two factors will be referred to as IUSFactor1 and IUSFactor2 respectively.

3.2.4 Uncertainty Tolerance Scale.

The UTS has a theoretical range from 8 to 48. Participant total scores on the UTS were normally distributed (n = 36, M = 26.97, SD = 5.16, and range = 13 to 39). Higher values are indicative of a greater tolerance to uncertainty.

3.2.5 General Decision-Making Style.

The GDMS yields five scores, one for each of the decision-making styles it investigates. The Rational, Dependent, Spontaneous, and Avoidant decision styles were normally distributed, but the Intuitive style was not, $W(32)$ = .93, p = .031. Each aggregate score is made up of five questions, except for Rational (for reasons mentioned in the methods section).

3.2.6 Endler Multidimensional Anxiety Scale – Trait scale.

The Trait scale of the EMAS yields a measure of trait-based anxiety along four situational dimensions: Physical Danger (PD), Social Evaluation (SE), Novel Situations (NS), and Daily Routines (DR). Each dimension ranges from 15 to 75 and every dimension was normally distributed except for Daily Routines, *W(32)* = .89, *p* = .002.

3.2.7 Fit indices.

Descriptive statistics for the fit indices can be found in Table 3. Tests of normality can be found in 3.1.5. Outliers, normality, and transformation.

Table 3

Descriptive Statistics for the Fit Indices by Model

	G^2			Pearson χ^2		
Model	*n*	*M* (*SD*)	range	*n*	*M* (*SD*)	range
Conditional	32	192.14 (117.25)	393.62	32	705.55 (783.48)	2878.81
Group	32	172.00 (106.25)	375.49	32	733.10 (832.51)	2994.37
Individualized	32	116.59 (60.19)	256.01	32	288.20 (294.79)	1102.35

3.2.8 Correlations.

Table 4 contains the bivariate correlations for all psychometric measures and the G^2 and Pearson χ^2 values for the Learners Group. As the majority of measures were normally distributed, Pearson’s correlation coefficient is reported for all. A Spearman’s rho correlation, not reported, found a consistent trend in the results and supported our use of Pearson’s correlation coefficient. All reported Pearson correlation coefficient significance tests are two-tailed.

DOC significantly correlated with GDMS-S (*r*[34] = -.428, *p* = .009), which represents that those who endorsed enjoying and desiring the use of cognition would be less likely to endorse a spontaneous approach to decision-making.

EMAS-PD significantly correlated with NFC (*r*[34] = -.458, *p* = .005), indicating that those who would prefer more cognitive control and have a greater tendency (and want) for thinking about problems possess lower levels of trait anxiety towards situations of PD. EMAS-PD also significantly correlated with GDMS-D (*r*[34] = .419, *p* = .011), GDMS-I (*r*[34] = -.429, *p* = .009) and GDMS-R (*r*[34] = .353, *p* = .035). These results indicate a positive relationship between having trait anxiety towards situations of PD and preferring others to assist in the decision-making process or make decisions for the individual, not wanting to rely on one's instincts to make decisions, and preferring to rationally contemplate a choice of action.

The IUS was also significantly correlated with the UTS (*r*[34] = -.410, *p* = .013), indicating that those endorsing a greater intolerance to uncertainty would be less likely to endorse being tolerant of uncertainty. In particular, the first factor of IUS was quite significantly correlated with the UTS (*r*[34] = -.396, *p* = .017), which means that those endorsing a lower tolerance (aversion) to uncertainty would desire more predictability and engage in activities which seek certainty.

The NFC was significantly correlated with the GDMS-D (*r*[34] = -.446, *p* = .006), indicating that those who would prefer more cognitive control and have a greater tendency (and want) for thinking about problems would be less likely to adopt a dependant decision making style.

A number of the decision-making styles in the GDMS have significant correlations with one another, indicative of individuals using a combination of decision-making styles. Significant correlations include: GDMS-D with GDMS-A (*r*[34] = ..660, *p* < .001), GDMS-S (*r*[34] = .442, *p* = .007), and GDMS-R (*r*[34] = .578, *p* < .001); GDMS-A with GDMS-S (*r*[34] = .371, *p* = .026), and GDMS-R (*r*[34] = .480, *p* = .003); and GDMS-S with GDMS-R (*r*[34] = .476, *p* = .003).

In a similar fashion to the canonical correlations, correlations between fit indexes found a highly positive correlation between Individualized G^2 and Pearson χ^2 values (*r*[34] = .922, *p* = < .001), between Group G^2 and Pearson χ^2 values (*r*[34] = .906, *p* = < .001), between Conditional G^2 and Pearson χ^2 values (*r*[34] = .469 *p* = .004), and between Group and Conditional G^2 (r[34] = .718, p < .001) and Pearson χ^2 values (*r*[34] = .940, *p* = < .001) respectively. No significant correlations between the Individualized model and the Group or Conditional models for either fit index were found.

The only significant correlations found with fit indexes and psychometric measures were between the EMAS-NS and both the Individualized model G^2 (*r*[34] =

.358, p = .032) and Pearson χ^2 (r[34] = .377, p = .023) values. This indicates that those who experience a higher degree of trait anxiety towards novel situations would be more inclined to deviate from the Conditional model's objective and the Group model's consensual utilities in favor of (personal) subjective utilities.

A number of significant correlations within the All Group overlap and have the same intuitive meaning with those in the Learners Group. Future sufficiency testing will consider disparate and similar responding between both groups to elucidate group differences. A correlation matrix for the All Group can be found in Appendix C for further consideration.

3.2.9 Canonical correlations.

A canonical correlation analysis was conducted in order to determine the relationship between the psychometric measures and the G^2 and Pearson χ^2 values across models. Two canonical correlations were conducted, one with the All Group and one with the Learners Group. No significant canonical correlations were found for either analysis. Following methodology outlined for Canonical Correlation (Neufeld, 1977), proportions of redundant variance were explored. By aggregating the redundancy indexes of the second set (fit indexes) by the first set (psychometric measures), the total variance accounted for by the first set can be enumerated. In the Learners group, the collect amount of variance was .403, making the average amount of variance accounted for by each (n=6) of the non-significant canonical correlations 6.7% of the variance.

Table 4

Correlation Matrix for Psychometric Measures and Fit Indices

	DOC	EMAS-PD	EMAS-SE	EMAS-NS	EMAS-DR	IUSTot	IUSF1	IUSF2	NFC	UTS	GDMS-D
DOC											
EMAS-PD	.00										
EMAS-SE	-.12	-.02									
EMAS-NS	.17	.25	.07								
EMAS-DR	-.27	.31	-.05	-.02							
IUSTot	-.01	.16	-.01	-.13	.29						
IUSF1	.06	.01	.03	-.06	.18	**.90**					
IUSF2	-.06	.17	-.08	-.20	.21	**.71**	.37				
NFC	.23	-.46	-.10	.16	-.24	-.21	-.05	-.30			
UTS	-.10	-.17	-.09	-2.8	.03	-.41	-.40	-.26	.13		
GDMS-D	-.25	.42	.15	.10	.20	.16	.06	.16	-.45	-.26	
GDMS-A	-.33	.16	.06	-.07	-.07	-.05	-.05	.00	-.23	-.14	**.66**
GDMS-S	-.43	.32	-.12	.21	.04	.20	.19	.04	-.24	-.18	.44
GDMS-I	.15	-.43	-.05	.05	-.23	-.02	.09	-.16	.30	-.06	-.19
GDMS-R	-.07	.35	-.11	.08	.08	-.04	-.04	-.04	-.13	-.15	**.58**
GInd	.10	.00	-.17	.36	-.11	-.33	-.26	-.25	.04	.05	.13
PInd	-.03	.18	-.12	.38	-.10	-.28	-.24	-.22	-.09	-.04	.26
GGroup	.22	.02	.04	.30	.15	-.09	-.10	.01	.08	-.05	.09
PGroup	.23	.16	.12	.29	.22	.13	.07	.12	.07	-.18	.08
GCon	.08	.01	-.06	.15	.27	.02	-.07	.14	-.08	.01	-.01
PCon	.25	.21	.17	.24	.20	.06	.02	.06	.05	-.14	.11

Underline indicates $p < .05$ (2-tailed); Boldface indicates $p < .001$(2-tailed).

DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, -F1: factor 1, -F2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for the Individualized model; PInd: Pearson χ^2 for Individualized model; GGroup: G^2 for the Group model; PGroup: Pearson χ^2 for Group model; GCon: G^2 for the Conditional model; PCon: Pearson χ^2 for Conditional model.

Table 5

Correlation Matrix for Psychometric Measures and Fit Indices (Continued)

	GDMS-A	GDMS-S	GDMS-I	GDMS-R	GInd	PInd	GGroup	PGroup	GCon
DOC									
EMAS-PD									
EMAS-SE									
EMAS-NS									
EMAS-DR									
IUSTot									
IUSF1									
IUSF2									
NFC									
UTS									
GDMS-D									
GDMS-A									
GDMS-S	.37								
GDMS-I	-.21	-.12							
GDMS-R	.48	.48	-.20						
GInd	.16	.04	.11	.07					
PInd	.24	.22	-.02	.13	**.92**				
GGroup	.08	-.26	-.07	-.19	.26	.12			
PGroup	-.02	-.22	-.12	-.24	.05	.02	**.91**		
GCon	-.05	-.17	-.03	*-.40*	-.01	-.07	**.72**	**.66**	
PCon	-.03	-.25	-.22	-.10	.06	.02	**.85**	**.94**	.47

Underline indicates $p < .05$ (2-tailed); Boldface indicates $p < .001$(2-tailed).
DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, -F1: factor 1, -F2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for the Individualized model; PInd: Pearson χ^2 for Individualized model; GGroup: G^2 for the Group model; PGroup: Pearson χ^2 for Group model; GCon: G^2 for the Conditional model; PCon: Pearson χ^2 for Conditional model.

Chapter 4: Discussion

4.1 Discussion for the Primary Purpose of the Study

Using a game-theoretic probability mixture-model created for our normative model of DC, sources of differential conformity between our collected participant data and the theoretical predictions posited by our formal normative model were explored. Specifically, the conformity or departure from the objective utilities imposed by the environmental framework were explored using three models of potential subjective utilities. The first model denoted the Conditional model, posited that participants would be perfect learners of the conditional probabilities of stressor occurrence from the Estes' (1976) paradigm and their subjective utilities would perfectly match the objective utilities.

Previous DC research has shown this not to be the case and have found that group averages of subjective utilities differ from the objective utilities one would except having learned the conditional probabilities (Lees & Neufeld, 1999; Morrison et al., 1988). As such, the second model, the Group model, had t_i values that were created through averaging pre- and post-Testing phase subjective probabilities. This was viewed as a logical way of accounting for departures in learning from the Estes' paradigm (1976) and learning was consistent with findings from previous DC studies using the same learning paradigm (Lees & Neufeld, 1999; Morrison et al., 1988). Another reason for using a Group model is that it allows the generalization of findings. It helps educe those item properties that did enter into subjects' formations of t_i (properties that were encoded at least in part), with an aim of generating consensus.

The final Individualized model used the participant's individually-specific, subjective utilities to investigate any departure from the normative model. Since the participant's own subjective utilities were used, the normative model would expect a perfect fit if it was being followed rigorously by participants. Incongruence under this model may be accounted for by varied decision-making styles or not perceiving accurately the experimental contingencies. The normative DC model assumes a maximizing/maximax strategy is adopted by participants, which may be true of some individuals and not of others.

Three different models of potential fit were investigated using G^2 and Pearson χ^2 fit indices. While there are many potential ways of assessing fit, both were selected as each allows statistical inference at the individual level. This is an important characteristic that will be required for future sufficiency testing and one which is advantageously used for the secondary aim of this current research. The use of G^2 is common place in model testing as maximum likelihood procedures are often favored over procedures using sum of squares (cf. Ashby, 1992; Wickens, 1982).

Results indicated that the Individualized model fit the participants responding significantly better than the Group and Conditional models. The departure of the Individualized model does leave us to believe that incorporating individual subjective utilities into our DC normative model is necessary to achieve the best fit. Results from both canonical correlations (between G^2 and Pearson $\chi 2$ variable sets) are in agreement with this statement. The first function when analyzing all participants (All Group; in Appendix B), found that subjectivity of the individual t_i values accounted for 92% of the variance shared between the two variable sets. The variance accounted for combined with the loading, imply that subjective utilities were the driving force of fit. As this canonical correlation included all participants (All Group), including those not included in the repeated measures ANOVA due to poor learning, it can be contrasted with the Learners Group. Comparing both canonical correlation's first factor, we see that the All Group's canonical loadings were specific to the Individualized model of t_i configurations alone, while in the Learners Group all three models had high canonical loadings. The interesting finding from the Learners Group, as mentioned in the methods section, was due to the directionality of the loadings. In the Learners Group, it appears that individuals who were kept for analysis either had t_i values that conformed somewhat to the objective and group t_i values or who consistently adhered to their subjective utilities (in the face of the environmental contingencies of stressor probability and likely many negative outcomes). These canonical loadings support the normative DC models use by individuals whose subjective utilities were in line with objective utilities. These individuals had learned to appropriately create optimal subjective utilities given Estes' learning paradigm (1976), were reinforced by the environmental framework of the normative model, and were able to assess and select MAX EU. Another subpopulation utilizing the normative DC model, but likely not performing as well (experiencing more stressor outcomes), were individuals who had departures in creating optimal subjective utilities given Estes' learning paradigm (1976), were or were not reinforced by the environmental framework of the normative model, but were able to select consistently the subjective utility they believed had MAX EU. Further research could investigate what dispositional and personality factors individuals in either group possessed, combined with outcomes of the environment, may have led these individuals to either learn to appropriately create SEUs or adhere to their SEUs while responding as the normative DC model theorized.

Considering our three groups, it is worth noting that we used the conditional (objective) probabilities as our normative representative throughout testing. Given that participants could been develop and operate off of a range of unforeseen utilities, the use of the normative probabilities was a limitation of the study that could bias participants in favor of its use. Especially as the conditional probabilities were fortified according to the credibility-maintaining delivery of stressor or innocuous event during the experimental trials. If anything entered into the participants cognitive mapping, it presumably would be the influence of the Conditional model objective probabilities. For example, considering the role of Bayes', one would assume that participants would pick up on the normative prescribed environmental cueing and being to conform to the objective probabilities (if they were not using these utilities already). Despite this, the findings supported the subjective utilities as the prevailing structure predicting selections.

Understanding what factors lead to the departure from the Conditional model to the Individualized one is relevant to improving person-environment interchange. Individuals may subjectively appraise one act as worse than another, but that does not make it so. In situations where being able to discern and utilize objective utilities is gravely important (e.g., in a combat scenario, flying a plane, hitting an ice patch while driving), a way is needed to help these individuals make better decisions. To have them learn and use objective utilities over subjective utilities. Departures from normative models are the result of DMs not being perfect rational beings. Comparing these three models allows us to empirically quantify the departure. These results necessarily inform the inclusion of subjective utilities in the present research and highlight that the group-averaged (consensus) subjective utilities conform more with the objective utilities. Future sufficiency research will investigate the critical values for each individual, under each model, necessary to identify a non-trivial departure. Further follow up work comparing individual critical values of fit and psychometric data, may better identify the characteristics of an individual with a high or low DC amenability.

The significant difference between the Individualized model and the other two models highlights the importance of considering SEUs when studying coping. In recent DC studies (Benn, 2001; Shanahan, 2016), participants were provided and learned the objective utilities that corresponded to the t_i values prior to model testing. Rigorously parsing out the subjectivity in stress and coping research may reduce the real-world applicability of the model. By incorporating the Estes' paradigm (1976), participants were able to form their own subjective utilities, which also allowed the three rules of a normative model to influence their decision. This was a strength of the current research. For example, the participants who were removed to form the Learners group may have had their subjective utilities change during the Testing phase due to inference under uncertainty (Edwards & Fasolo, 2001). It is possible that poor performance during the Testing phase coupled with potential personal factors (e.g., trait anxiety to novel situations, intolerance of uncertainty, etc.) brought about dynamic updating (re-appraisal) of SEUs. It does not mean that the DC normative model was not at work, it might be that the subjective utilities had not be concretely mapped for these participants and more readily changed.

Purposefully, the Testing phase was broken into three blocks of identical, but randomly ordered trials. In future research, outcomes (benign or with a stressor) and their relation to dynamical updating and personality variables will be investigated. It may be possible to illustrate when a cognitive re-appraisal occurs during the blocks and accounts for differences seen in pre- and post-Testing phase subjective probabilities. As well, identifying these areas of interest could lend further support our normative model of DC, by allowing responses to be recoded due to subjective re-appraisal of MAX EU values between and during Testing phase blocks. The inclusion a measures which tap participant's confidence in their rated subjective probabilities and queries self-reported re-appraisal of SEUs during the session would be recommended inclusions for future research.

Currently, a limitation of using an averaged (consensus) score consisting of pre- and post- subjective probabilities is that rank orderings may have differed throughout the Testing phase blocks. An average value also limits our understanding of the magnitude of the re-appraisal which occurred. For example, a participant may rightly believe that letter J possesses the MAX EU and is followed by a stressor roughly 10% of the time after completing the Learning phase. After the first block of the Testing phase, which may have contained many instances of selecting J and receiving the stressor, the participant may update their subjective utility to believe J is followed by a stressor 60% of the time. Continuing to work on this belief through the next two blocks, they report that J is followed by a stressor 60% of the time on the post-Testing phase probability rating sheet. An average of these two probabilities leads to a score of 35%, which may situate J as their t_3 value. Responding across the first block where J was their t_1 value and across the next two blocks where J was possibly their t_5 value may conform to our DC normative model predictions, but not be captured properly by the averaging. In essence, the averaging of these rating sheets, while the best choice at attempting to understand their subjective utilities and common, may increase departure from the DC normative model. For this reason, only participants with strong internal consistency (as evaluated by Spearman's rank correlations), and presumably a small magnitude of change pre- and post-Testing phase, were included in the repeated measures ANOVA. While this is likely to minimize its effect on our results, it cannot be disregarded altogether. Results should be considered with this limitation in mind until future sufficiency testing on this data can assist in evaluating how well individuals conform to the DC normative model.

In the Individualized model, individuals varied in the size of their fit estimate. As alluded to in previous sections, this departure can be due to sub-optimal decision-making styles. The DC model assumes that DMs will utilize a maximizing/maximax strategy and make a choice at a node that potentially leads to the minimally available t_i. From the range of fit scores, this may not be true of all individuals. Further analyses would deconstruct the aggregate fit indices into their nine different architectures (j) and explore in what situations, where DC is available, do participants select the minimally available t_i. These results will be further augmented with analyses investigating response time and psychophysiological indices of stress generation. Based on prior DC research (Shanahan et al., 2012; Shanahan & Neufeld, 2010), *U* at a subordinate node leads to higher stress generation and more contemplation. It is possible to disentangle those individuals who exhaustively search for and select the MAX EU as one would expect from a maximizer using the gathered empirical sources of corroborating data in this research. By investigating these individuals' data, we can hope to discern what about this group of DMs makes them more likely to adopt a maximizing decision-making style.

With regards to testing the model using participant responses, the DC normative model's theoretically prescribed probabilities for responding can be adjusted to fit the data. Currently the normative model assumes a very rigid degree of conformity that does not allow for decision-making styles other than maximizing/maximax. Using the Individualized model, whereby strategy per se is thrown into relief, these theoretical predictions can be relaxed and aligned with typical responding (accounting for other decision-making styles). By doing so, the model can more accurately capture normative stress-coping and attempts at replication with a new sample are possibilities.

4.2 Discussion for the Secondary Purpose of the Study.

In order to investigate sources of departure from the normative DC model, correlations were run between measures used in previous DC research and presumed to have role in decision-making, disposition towards uncertainty and fit indices. While a number of significant correlations were found between psychometric measures, decidedly fewer significant correlations were found between psychometric measures and fit indices.

A canonical correlation was run between the fit indices and the psychometric measures in an effort to identify measures which account for a large proportion of variance seen between fit indices. Results were non-significant and redundancy indexes did not account for much variance. There were a couple notable significant correlations between trait anxiety to novel situations and both fit values for the Individualized model, as well as interesting trends between fit indices. However, based on the relatively small value from aggregating the redundancy indexes and due to the paucity of bivariate correlations found, speculations and judgements will be withheld until future studies can address personality variables in a confirmatory way. For example, future research could include running this canonical correlation again between individuals who are identified by sufficiency testing as applicable users of the normative DC model and those who did not sufficiently use the model. Lastly, it is noteworthy that the bivariate collection array is exploratory, as there is no provision for multiple tests on the individual conditions (cf. Larzelere & Mulaik, 1977).

Chapter 5: Conclusions

In pursuit of necessity testing the normative DC model, the Individualized model was found to be significantly better than both the Conditional and Group models. As such, for the normative DC model to operate in conditions amenable to its use, subjective t_i values unique to each individual must be collected and used in creating fit indices. Individual differences in fit were not tapped by the selected psychometric measures and possibly lay outside of the personality domain. Future sufficiency testing used to identify conditions, decision-making styles (maximizers or satisficers) and psychometric correlates which are sufficient for the function of the normative DC model will require the use of subjective utilities.

As the first DC study to use frequency data in order to construct multinomial likelihood ratios with the aim of evaluating goodness-of-fit (and also contrasting these results with Pearson's χ^2 values of fit), this study has identified the necessary components of model fit to be considered for future research. With our novel mixture model architecture, we are also well situated for subsequent sufficiency testing.

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Appendices

Appendix A: Formulae for the Probabilities of Engaging Decisional Control structure element *i*, Pr(t_i)

$$Pr\left(t_i\right)_{CC;\,pq} = \begin{cases} 1.0 & \textbf{if} \quad i = 1 \\ 0 & otherwise \end{cases}.$$

$$Pr\left(t_i\right)_{CU;\,pq} = \begin{cases} \dfrac{1}{q} & \textbf{if} \quad i = 1 \\ \dfrac{(q-1)}{q(pq-1)} & \textbf{if} \ i = 2, \ldots, pq \end{cases}.$$

$$Pr\left(t_i\right)_{CN;\,pq} = \begin{cases} \dfrac{\binom{pq-i}{p-1}}{\binom{pq}{p}} & \textbf{if} \ i \leq p\,(q-1)+1 \\ 0 & otherwise \end{cases}.$$

$$Pr\left(t_i\right)_{UC;\,pq} = \begin{cases} \dfrac{\binom{pq-i}{q-1}}{\binom{pq}{q}} & \textbf{if} \ i \leq q(p-1)+1 \\ 0 & otherwise \end{cases}.$$

$$Pr\left(t_i\right)_{UU;\,pq} = \frac{1}{pq}.$$

$$Pr\left(t_i\right)_{UN;\,pq} = \frac{1}{pq}.$$

$$Pr\left(t_i\right)_{NC;\,pq} = \begin{cases} \dfrac{\dbinom{pq-i}{q-1}}{\dbinom{pq}{q}} & \textbf{if} \quad i \le q(p-1)+1 \\ 0 & \qquad otherwise \end{cases} .$$

$$Pr\left(t_i\right)_{NU;\,pq} = \frac{1}{pq}.$$

$$Pr\left(t_i\right)_{NN;\,pq} = \frac{1}{pq} .$$

Appendix B: All Group Canonical Correlations

Results for the All Group indicated that three significant canonical functions emerged, $R_c = .964$, Wilk's $\Lambda = .007$, $F(9, 97.5) = 71.50$, $p < .001$, for function 1; $R_c = .927$, Wilk's $\Lambda = .101$, $F(4, 82.00) = 44.14$, $p < .001$, for function 2; and $R_c = .532$, Wilk's $\Lambda = .717$, $F(1, 42.00) = 16.58$, $p < .001$, for function 3. As Wilk's Λ represents the variance unexplained by the model and 1- Λ gives us the full model effect size in r^2, the full model explained about 99.3% of the variance shared between the two variable sets. Given that the R_c^2 effects for the first two functions accounted for 92% and 86% of shared variance respectively, only the first two functions were considered relevant in the context of the study.

The only variable in the first set that loaded onto the first function was the G^2 value for the Individualized Model (.889) and the only variable from the second set that loaded was the Pearson χ^2 value for the Individualized Model (.887). The redundancy indices for the first and second set were .249 and .251 respectively. From these results, it appears the first function demonstrates a link between both measures of Individualized model fit and accounts for variance unique to the use of subjective t_i values. Thus, it can be inferred that t_i values are related the first canonical correlation.

In the second function, both the G^2 value for the Group Model (.996) and the G^2 value for the Conditional Model (.670) from the first set loaded, as did both the Pearson χ^2 value for the Group Model (.983) and the Pearson χ^2 value for the Conditional Model (.963) in the second set. The redundancy indices for the first and second set were .471 and .597 respectively. From these results, it appears the second function demonstrates a link between both measures of Group and Conditional Model fit and accounts for variance shared between the Group and Conditional orderings of t_i values. It is worth pointing out that this variance is orthogonal to the variance accounted for by both measures of Individualized Model fit.

Appendix C: All Group Correlation Matrix for Psychometric Measures and Fit Indices

	DOC	EMAS-PD	EMAS-SE	EMAS-NS	EMAS-DR	IUSTot	IUSF1	IUSF2	NFC	UTS	GDMS-D
DOC											
EMAS-PD	.07										
EMAS-SE	.02	.10									
EMAS-NS	.12	.30	.08								
EMAS-DR	-.25	.30	-.05	.16							
IUSTot	-.01	.29	.05	.21	.42						
IUSF1	.06	.15	.08	.15	.28	**.90**					
IUSF2	-.09	.28	-.03	.21	.39	**.84**	**.54**				
NFC	.14	-.44	-.23	-.18	-.32	-.39	-.21	-.44			
UTS	-.08	-.09	-.11	-.24	.00	-.35	-.40	-.18	.21		
GDMS-D	-.25	.32	.10	-.06	.12	.01	-.01	-.02	-.20	-.17	
GDMS-A	-.14	.12	.00	-.10	-.10	-.08	-.05	-.07	.05	-.01	**.61**
GDMS-S	-.32	.21	-.02	.14	.06	.18	.17	.08	-.13	-.12	.42
GDMS-I	.20	-.14	-.04	.05	-.14	.10	.12	.06	.14	.03	-.21
GDMS-R	.05	.28	-.01	.11	.12	.02	.01	-.01	-.13	-.14	**.50**
GInd	.13	.10	-.11	.08	-.09	-.06	.00	-.12	-.07	-.12	-.03
PInd	-.01	.22	-.08	.16	-.02	.05	.08	-.01	-.19	-.19	.03
GGroup	.25	.15	.12	.27	.15	.09	.07	.09	-.11	-.15	-.04
PGroup	.24	.19	.15	.25	.21	.18	.16	.12	-.07	-.24	-.02
GCon	.11	.08	.01	.16	.27	.10	.02	.14	-.14	-.03	-.05
PCon	.22	.27	.20	.30	.25	.25	.20	.21	-.19	-.23	-.04

Underline indicates $p < .05$ (2-tailed); Boldface indicates $p < .001$(2-tailed).
DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, -F1: factor 1, -F2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for the Individualized model; PInd: Pearson χ^2 for Individualized model; GGroup: G^2 for the Group model; PGroup: Pearson χ^2 for Group model; GCon: G^2 for the Conditional model; PCon: Pearson χ^2 for Conditional model.

Appendix D: All Group Correlation Matrix for Psychometric Measures and Fit Indices (continued)

	GDMS-A	GDMS-S	GDMS-I	GDMS-R	GInd	PInd	GGroup	PGroup	GCon
DOC									
EMAS-PD									
EMAS-SE									
EMAS-NS									
EMAS-DR									
IUSTot									
IUSF1									
IUSF2									
NFC									
UTS									
GDMS-D									
GDMS-A									
GDMS-S	<u>.42</u>								
GDMS-I	-.19	-.19							
GDMS-R	<u>.47</u>	<u>.49</u>	-.19						
GInd	-.12	-.27	.24	-.06					
PInd	-.16	-.20	.16	-.06	**.95**				
GGroup	-.13	<u>-.33</u>	.07	-.17	<u>.48</u>	<u>.44</u>			
PGroup	-.19	<u>-.30</u>	-.01	-.23	<u>.29</u>	<u>.30</u>	**.91**		
GCon	-.12	-.20	.03	<u>-.36</u>	.13	.12	**.72**	**.68**	
PCon	-.25	<u>-.30</u>	-.06	-.10	<u>.33</u>	<u>.37</u>	**.88**	**.93**	**.51**

Underline indicates $p < .05$ (2-tailed); Boldface indicates $p < .001$(2-tailed).
DOC: Desirability of Control; EMAS: Endler Multidimensional Anxiety Scale – Trait Scale, -PD: Physical Danger, -SE: Social Evaluation, -NS: Novel Situations, -DR: Daily Routines; IUSTot: Intolerance of Uncertainty total score, -F1: factor 1, -F2: factor 2; NFC: Need for Cognition; UTS: Uncertainty Tolerance Scale; GDMS: General Decision-Making Scale, -D: Dependent, -A: Avoidant, -S: Spontaneous, -I: Intuitive, -R: Rational; GInd: G^2 for the Individualized model; PInd: Pearson χ^2 for Individualized model; GGroup: G^2 for the Group model; PGroup: Pearson χ^2 for Group model; GCon: G^2 for the Conditional model; PCon: Pearson χ^2 for Conditional model.

Appendix E: Probability Rating Sheet

Judgement Phase **1**:

Letter

______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100
______	0	25%	50%	75%	100

Appendix F: Rank Ordering Sheet

Rank Ordering Judgement 1:

Please rank these 10 letters in order from LOWEST to HIGHEST probability of being followed by a noise:

V Z L J B D P G M A

Lowest **Highest**

____ ____ ____ ____ ____ ____ ____ ____ ____ ____

Appendix F Letter of Information

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control
Principal Investigator: Dr. Richard Neufeld, PhD, Psychology, Western University
Co-investigator: Bryan Grant, BSc, Psychology, Western University

Letter of Information

1. **Invitation to Participate**
   You are being asked to take part in a study investigating how people make decisions when faced with stressful situations. Discerning how individuals judge alternatives when faced with a host of aversive events and exert personal control to minimize the anticipated stress can increase our understanding of the cognitive underpinnings of stress.

2. **Purpose of the Letter**
   The purpose of this letter is to provide you with information required for you to make an informed decision regarding participation in this research and stimulate any questions you may have concerning your participation.

3. **Purpose of this Study**
   Stress is a universally experienced phenomenon, but we have yet to understand why stress is generated in response to varying situations. How one assesses stressful situations and the degree to which stress is experienced when control is limited is the target for this study.
   Stress has cognitive, psychophysiological, and behavioural components – thinking about stressful situations and ways of coping, reacting with physical changes (heart rate, sweating, muscle agitation, etc), and choosing what to do – all factor into how stress is experienced and coped with. “Decisional Control” is a method of coping with stress in which the decision maker chooses to insert himself or herself into a stressful situation in order to avoid other situations with higher probabilities of a stressful occurrence. The underlying assumption is that a decision maker, when faced with a selection of varying levels of adverse events, will make judgements (a cognitively-intensive process using learned probabilities) about the stress inherent in each situation and choose available options accordingly. In other words, when an individual is given a choice, he or she will attempt to choose the situation with the least likelihood of producing a bad outcome (with the likelihood being based on previous experience of the bad outcome happening or not). Deciding which situation is the least likely to produce the most stress requires some planning and knowledge about the probabilities that something will go wrong; this, of course, is a thought-intensive process.
   One way of conceptualizing and testing this “decisional control” coping strategy is to use a “game-theoretic approach” whereby stress negotiation is envisioned as playing a “game” with created scenarios. These scenarios combine to form a model (a “game-theoretic infrastructure”), that is used to predict how people are

likely to respond in stressful situations. The model can be thought of as the "board" and the parameters as the "rules". Assuming that people are following the rules and playing using this game-theoretic infrastructure, we are able to predict the advantageous decisions they would make to achieve the best result. One such game-theoretic infrastructure has been created by this lab and simulation work has predicted how people should respond. However, to validate this infrastructure, we need to know if our predictions align with how people actually respond. Thus, the intended purposes of this study are as follows:

1) To compare our generated model's probability predictions to participants' actual behaviour, in order to see how well the model predictions accurately describe real responses.

2) To gather data to support this decisional control infrastructure and explore individual differences in responding to stress. These differences may include behavioral (e.g., what people select and the time taken to make these selections), psychophysiological (e.g., heart rate, skin conductance) and subjective measures (e.g., verbal reports about how stressful making selections was through the use of numerical ratings).

By empirically gathering data and modelling behavioural, cognitive and psychophysiological responses to stressful scenarios, we can generate a picture for how people actually do respond. By further incorporating the use of psychometric questionnaires (e.g. personality measures, intelligence tests, preferred methods of coping, etc), individual differences in how decisional control was applied will create a richer picture of how individuals cope with stress. We are also interested in how people in a group respond; by combining all the individual responses, we are able to map out a range of responses that can provide an idea of how a variety of people in a group might respond. In this way, the model will be tested not only at an individual level but also at a group level.

4. Inclusion Criteria

Individuals who are under 30 years old, right handed, have no hearing problems and good English reading comprehension are eligible to participate in this study.

5. Exclusion Criteria

Non-consenting individuals and those who are 30 years old or older, left handed, having hearing problems or do not have good English reading comprehension are not eligible to participate in this study.

6. Study Procedures

This experiment includes a questionnaire phase, a learning phase, a practice phase and a test phase. Before giving consent, you will be briefly exposed to 1 seconds of white noise calibrated to a maximum of 85 decibels (about the noise of a subway car 200 feet away). If you have a hearing impairment or sensitivity, please let the experimenter know, as it is not advisable to continue with the experiment in this case. Prior to giving and documenting written consent, you will hear the 1 second sample of white noise, so that you will know what it sounds like.

In the first phase of the experiment, you will be asked to complete several questionnaires about personality, coping, and decision-making. This should take between 15 and 30 minutes.

For the second phase and third phases, you will be tutored by a set of computer instructions and learning screens and then asked to practice decision-making tasks on the computer (a total of about 45 minutes). During the learning phase, you will learn to associate the probability of a 1 second sample of the white noise, or a green computer screen, for a set of 10 random letters.

Before beginning the next phase, you will receive a brief introduction to the experimental apparatus and fitted by a same-sex research assistant (or choose to apply yourself) with 4 electrodes: one on the neck, one above the ankle, and two on fingers of your left-hand. Depending on the region and in order to attach these electrodes, it may be necessary for you to move or lift the collar of your shirt and/or your pant leg (only during their application and removal of these electrodes). These electrodes are disposable and are only used for one participant and discarded. These electrodes are for detecting a signal and are incapable of delivering a shock.

During the proceeding test phase, the 10 random letters from the learning phase will be presented again for selection in a computer-driven game-theoretic model. These trials presented on the computer will be structures with letters arranged on the bottom that you will have varying amount of control over. You will be asked to consider the layout of these structures and choose a letter available for selection. Upon selection of a letter, you will either experience the white-noise or green-light event based on the probability you learnt in the practice screens. As such, you will experience brief (1 second) instances of the white noise or green light again throughout this phase. In consultation with the Department of Communication Disorders and in keeping with Ontario Ministry of Labour guidelines, this noise exposure is not considered to be harmful in the short duration it will be administered for individuals with normal hearing.

The total amount of time involved for completion of the study is about three to four hours over this 1 session in room 6b of Westminster Hall. You can choose to take part in the entire session or stop at any particular 30 min (approx.) block. Please note that you will be compensated on a pro-rated amount based on how much of the study you complete (see Compensation below). By agreeing to take part in this study, you will be one of a total of 80 participants.

7. Possible Risks and Harms

Part of the experiment is to present you with minimal discomfort (i.e., brief exposure to annoying or aversive "white noise”) in order to generate occurrences of varying levels of stress. However, there are no known physical or psychological risks involved and such noise is designed not to harm your hearing. This stimulus is somewhat standard in this type of study and has been used in past studies in this lab.

8. **Possible Benefits**
   You may not directly benefit from participating in this study but information gathered may provide benefits to society as a whole by increasing our understanding of individual responding in making choices under stress conditions.

9. **Compensation**
   For those in Psych 1000: You will be compensated up to 4 research credits for your participation in this study. If you do not complete the entire study you will still be compensated at a pro-rated amount of 0.5 credit per half hour of participation.
   For those in other courses with a research component: You will be compensated according to the criteria set forth on your course syllabus. Please consult your specific course outline for details of your compensation.

10. **Voluntary Participation**
    Participation in this study is voluntary. You may refuse to participate, refuse to answer any questions or withdraw from the study at any time with no effect on your future academic status and without loss of promised pro-rated compensation.

11. **Confidentiality**
    All data collected, which will be stored by code (and not by name) to protect your privacy, will remain confidential and accessible only to the investigators of this study. The coded data will be stored on a computer hard drive, an external hard drive, and in a locked cabinet all within locked offices. The list of participants' names with their corresponding codes will be stored in a separate locked place. If the results are published, your name will not be used. If you choose to withdraw from this study, your data will be removed and destroyed from our database. All data will be destroyed five years after publication. While we will do our best to protect your information there is no guarantee that we will be able to do so. The inclusion of your initials and your age (years and months) may allow someone to link the data and identify you.

12. **Contacts for Further Information**
    If you require any further information regarding this research project or your participation in the study you may contact Dr. Neufeld [redacted], or Bryan Grant, [redacted]). If you have any questions about your rights as a research participant or the conduct of this study, you may contact The Office of Research Ethics [redacted]

13. Publication

In publication of results of the study, your name will not be used. If you would like to receive a copy of any potential study results, please provide your name and contact information on the sheet entitled Consent to Contact with Results included in this package.

This letter is yours to keep for future reference.

Consent Form

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control

Study Investigator's Name: Dr. Richard Neufeld, PhD, Psychology, Western University

I have read the Letter of Information, have had the nature of the study explained to me and I agree to participate. All questions have been answered to my satisfaction.

Participant's Name (please print): ____

Participant's Signature: ____

Date: ____

Person Obtaining Informed Consent (please print): ________________________________

Signature:______________________________

Date: _______________________________

Appendix G: SONA Outline

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control

Principal Investigator: Dr. Richard Neufeld, PhD, Psychology, Western University

Co-investigator: Bryan Grant, BSc, Psychology, Western University

<u>SONA template:</u>

In this study, you will be asked to complete a number of personality questionnaires and a decision making computer task (where you will make selections based on several choices available). During the computer task, you will have psychophysiological-measuring electrodes attached by a same-sex research assistant to your neck, breastbone, and upper and lower rib cage. As such, we ask that you wear a loose, short-sleeved shirt when you attend the testing session; this will enable the same-sex research assistant to attach the electrodes without needing you to remove your shirt entirely. To generate some stress in completing the decision making computer task, you will experience quick, one second bursts of loud noise (roughly equivalent to a passing subway car) throughout the study based on a combination of probability and performance. Please note, that the use of this noise is kept at safe levels and with a total length well below what is advised by Ontario's Ministry of Labour guidelines for exposure in loud environments.

The study will take between 3 and 4 hours (based on how long you would like to participate) and will take place in [redacted] If you are a Psychology 1000 student, you will receive 0.5 credits toward your Psychology 1000 research participation option for each half hour of the study.

In order to participate in this study, you must be right handed, have good reading comprehension and are younger than 30 years old.

If you have any questions about the study, please contact Bryan Grant at [redacted]

Please note: your participation is voluntary and all information collected will be kept confidential.

<u>Email correspondence:</u>

Subject Line: Invitation to participate in research

You are being invited to participate in a study that explores the physiological and behavioural effects of stress on decision making. This email is a courtesy message briefly detailing the study before you come in for your selected session time in [redacted] During this meeting you will go over the letter of information, establish consent and complete the study if you choose to consent. This is a reminder that you are able to take part in the study only if you are right handed, have good reading comprehension and are younger than 30 years old.

The study can take between 3 and 4 hours to complete and its length is based on how many blocks of the experiment you would like to complete. For participating in the study, you will receive credits towards your course requirements on a prorated amount based on the amount of the study that has been completed. For example, if you are in Psych 1000, you will receive half a credit for every half an hour of the study you complete up to a total of 4 credits. For other courses, please see your course syllabus for criteria on how you will receive credits for participation.

In the study, you will required to complete a number of personality questionnaires (on how you respond to stressful/anxiety provoking situations) and a decision making computer task (where you will make selections based on several choices available). During the computer task, you will have psychophysiological-measuring electrodes attached by a same-sex research assistant to your neck, breastbone, and upper and lower rib cage. As such, we ask that you wear a loose, short-sleeved shirt when you attend the testing session as this will enable the same-sex research assistant to attach the electrodes without needing you to remove your shirt entirely. To generate some stress in completing the decision making computer task, you will experience quick, one second bursts of loud noise (roughly equivalent to a passing subway car) throughout the study based on combination of probability and performance. Please note, that the use of this noise is kept at safe levels and with a total length well below what is advised by Ontario's Ministry of Labour guidelines to exposure for loud environments.
To aid you in finding the testing room, a research assistant will you meet you in the main lobby of Westminster Hall a few minutes before your testing session.

If you have any further questions about the study, do not hesitate to ask them in a reply to this email.

Thank you,Dr. Richard Neufeld

Western University

[redacted]

Bryan Grant

Western University

[redacted]

Appendix H: Debriefing Sheet

Project Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control

Principal Investigator: Dr. Richard Neufeld, PhD, Psychology, Western University

Co-investigator: Bryan Grant, BSc, Psychology, Western University

Decisional Coping Experimental Debrief Sheet

This study you have just participated in was concerned with how people react when under the effects of stress. Coping with stress is a universal experience and, undoubtedly, one that requires a complex interplay of cognitive functions. Coping with stress can be done in a variety of ways, but choice is key in determining how an individual will respond (Averill, 1973). Through behavioural, cognitive and decisional means, choice in stressful situations offers an advantage of accessing less-threatening alternatives and greater control of reducing stress reactions (Averill, 1973).

Decisional Control is a method of coping with stress in which the decision maker positions "oneself in a stressor situation so as to avoid situational components harboring higher probabilities of stress" (Lees & Neufeld, 1999, p. 185) from a physically or socially adverse event. The underlying assumption is that a decision maker, when faced with a selection of varying levels of adverse events, will make probabilistic judgements (a cognitively-intensive process) about the stress inherent in each situation and make a choice to pursue the option they believe has the lowest associated level of stress.

The paradigm you completed on the computer was one in which decisional control was conceptualized and tested through a game-theoretic approach whereby stress negotiation is cast as playing a game with the environment, the goal of which is to maximize well-being or safety. The stressor used in the experiment was the administration of loud white noise. You were presented with choices involving selection of letters that represented a threat level. Selections varied to some extent in the degree to which they were controllable (i.e., sometimes you were given only one selection and other times you were allowed to make your own choice).

The first aim of this study is to test this game-theoretic infrastructure upon which a mathematical model (technically a probability mixture model) was built. Such an infrastructure (or representative environmental framework) would allow us to develop precise likelihoods of stress-relevant events and test our model at both an individual and group level. If our model predictions align with empirical observations, the model could be adapted for use in future studies with clinical populations with known cognitive and decisional difficulties. This could allow theoretical exploration and interpretation of aberrant or dysfunctional cognition leading to suboptimal, cognition dependant coping strategies in these groups.

In order to quantify and empirically test this environmental framework of decisional control and explore individual differences in responding, behavioural (e.g., choice selection and their latencies), psychophysiological (e.g., heart rate, skin conductance, facial muscle responses) and subjective measures (e.g., verbal reports, numerical ratings) of stress were collected from you. Past research has supported the use of these empirical measures quantifying decisional control composition (reviewed in Shanahan & Neufeld, 2010).

The second aim of this study is to explore how people differ in the way in which they react to similar situations. That is, not all people find controllable situations to be less stressful than uncontrollable situations. In fact, some people may actually find controllable situations to be more stressful than uncontrollable ones. This study was designed to examine the preferences people have about the different kinds of stressful situations they might find themselves in indicative of their decisional coping style. The model will be further augmented with individual-difference psychometric analyses (participants competing personality measures) to explore individual aptitude differences in application of decisional control. The resultant findings will give rise to new model-testing predictions including how individuals use decisional control to varying degrees in making decisions.

If you find you are having trouble managing stress in your own life, or have been upset by anything in particular during this experiment, please let the experimenter know. Two counseling resources available for students include the:

[redacted]

If you have any questions about the experiment which were not answered during or after the experiment itself, feel free to contact Bryan Grant, [redacted], [redacted] or Prof. Richard W.J. Neufeld, [redacted] [redacted] If you have questions about your rights as a research participant, you should contact the Director of the Office of Research Ethics at [redacted]

Thank you very much for your participation.

References

Averill, J. R. (1973). Personal control over aversive stimuli and its relationship to stress. *Psychological Bulletin, 80,* 286-303.

Lees, M.C., & Neufeld, R.W.J. (1999). Decision-theoretic aspects of stress arousal and coping propensity. *Journal of Personality and Social Psychology, 77*, 185-208.

Shanahan, M.J., & Neufeld, R.W.J. (2010). Coping with stress through decisional control: Quantification of negotiating the environment. *British Journal of Mathematical and Statistical Psychology*, *63*, 575-601.

For further readings, please consult:

Neufeld, R.W.J. (1999). Dynamic differentials of stress and coping. *Psychological Review*, *106*, 385-397.

Levy, L.R., Yao, W., McGuire, M., Vollick, D.N., Jetté, J., Shanahan, M.J., Hay, J. & Neufeld, R.W.J. (2012). Nonlinear bifurcations of psychological stress negotiation: New properties of a formal dynamical model. *Nonlinear Dynamics, Psychology and Life Sciences*, *16*, 429-456.

Appendix I: Ethics Approval

Western Research

Research Ethics

Western University Health Science Research Ethics Board
NMREB Delegated Initial Approval Notice

Principal Investigator: Prof. Richard Neufeld
Department & Institution: Schulich School of Medicine and Dentistry\Psychiatry,Western University

NMREB File Number: 106993
Study Title: Individual Differences in Stress and Coping: Testing a Model of Decisional Control
Sponsor:

NMREB Initial Approval Date: August 27, 2015
NMREB Expiry Date: August 27, 2016

Documents Approved and/or Received for Information:

Document Name	Comments	Version Date
Instruments	Need for Cognition	2015/07/19
Instruments	Uncertainty Tolerance Scale	2015/07/19
Instruments	Intolerance of Uncertainty Scale Short Version	2015/07/19
Instruments	Monitoring Blunting Questionnaire	2015/07/19
Instruments	Endler Multidimensional Anxiety Scales	2015/07/19
Instruments	Internal Control Index	2015/07/19
Instruments	Desirability of Control	2015/07/19
Other	Consent to Contact Form	2015/07/19
Revised Western University Protocol		2015/08/03
Other	Debriefing Sheet	2015/08/03
Revised Letter of Information & Consent	Letter of Information	2015/08/03
Other	SONA Outline	2015/08/03

The Western University Non-Medical Research Ethics Board (NMREB) has reviewed and approved the above named study, as of the NMREB Initial Approval Date noted above.

NMREB approval for this study remains valid until the NMREB Expiry Date noted above, conditional to timely submission and acceptance of NMREB Continuing Ethics Review.

The Western University NMREB operates in compliance with the Tri-Council Policy Statement Ethical Conduct for Research Involving Humans (TCPS2), the Ontario Personal Health Information Protection Act (PHIPA, 2004), and the applicable laws and regulations of Ontario.

Members of the NMREB who are named as Investigators in research studies do not participate in discussions related to, nor vote on such studies when they are presented to the REB.

The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

[redacted]ir or delegated board member

Ethics Officer to Contact for Further Information

Erika Basile	Grace Kelly	Mina Mekhail	Vikki Tran
[redacted]			

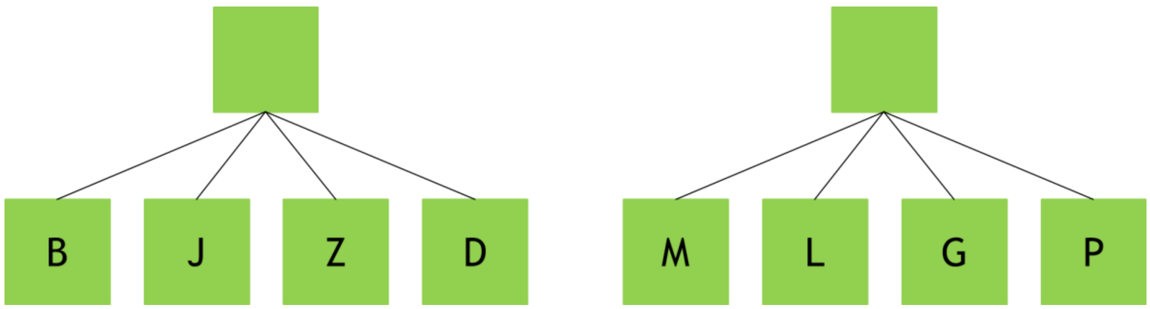
This is an official document. Please retain the original in your files.

Western University, Research, Support Services Bldg., Rm. 5150
London, ON, Canada N6G 1G9 t. 519.661.3036 f. 519.850.2466 www.uwo.ca/research/ethics

Appendix J: Hierarchal Structures Presented During Testing

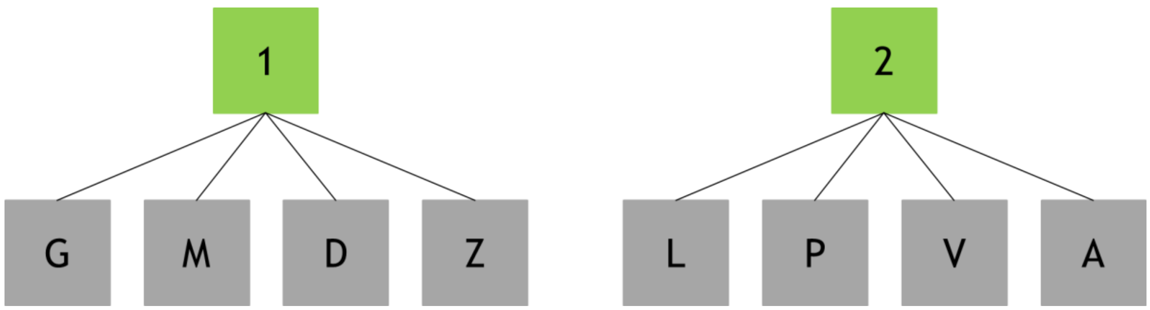
Note: The eight letters presented at the bin level were completely randomized each trial and random, static letters are presented below for example purposes.

CC:



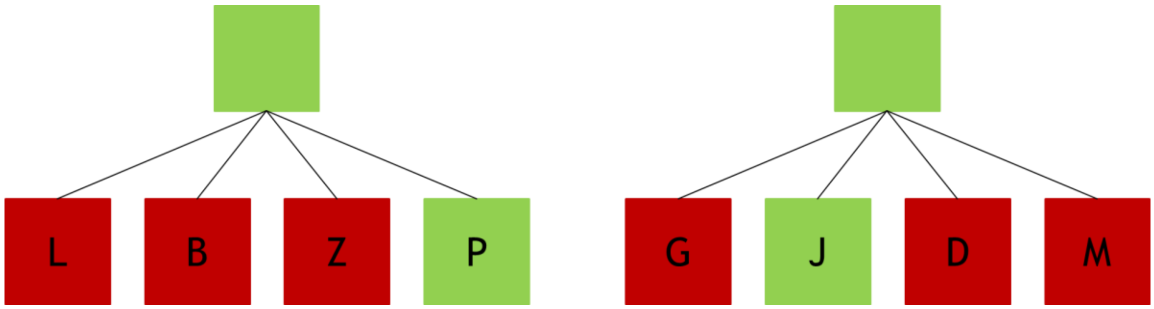
In a CC condition, participants have information and control at both the bin and element level. They can select any letter within either group.

CU:



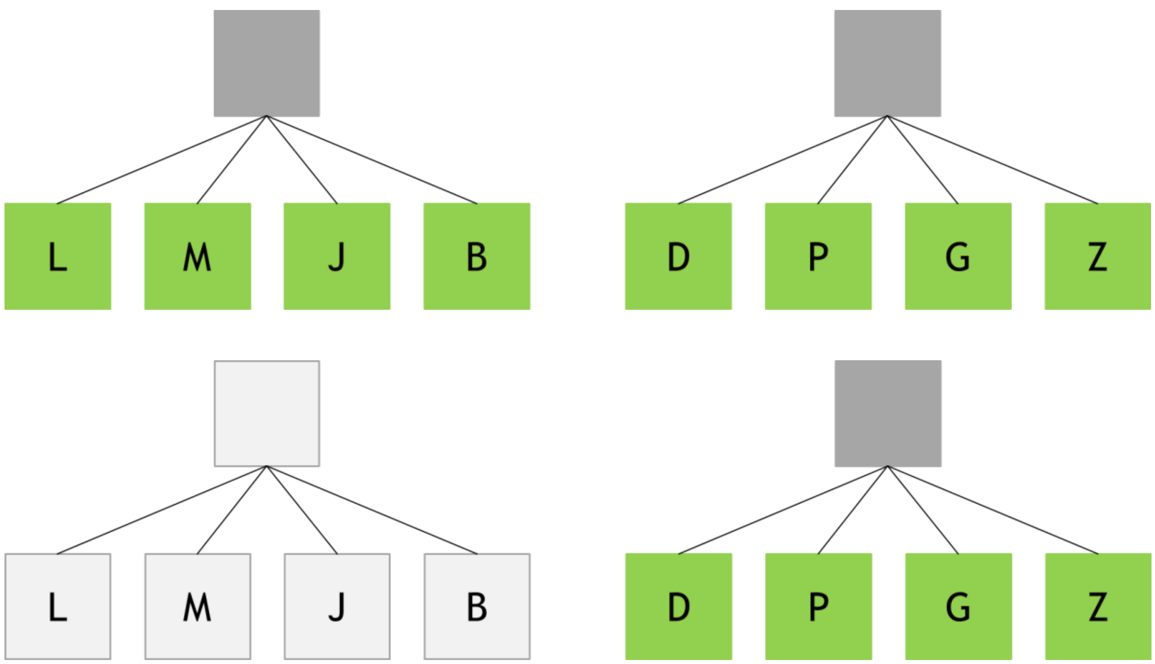
In a CU condition, participants have information and control at the element level, but neither control or information at the bin level. They can select either group (pressing 1 or 2), but a letter at random within that group is assigned to them.

CN:



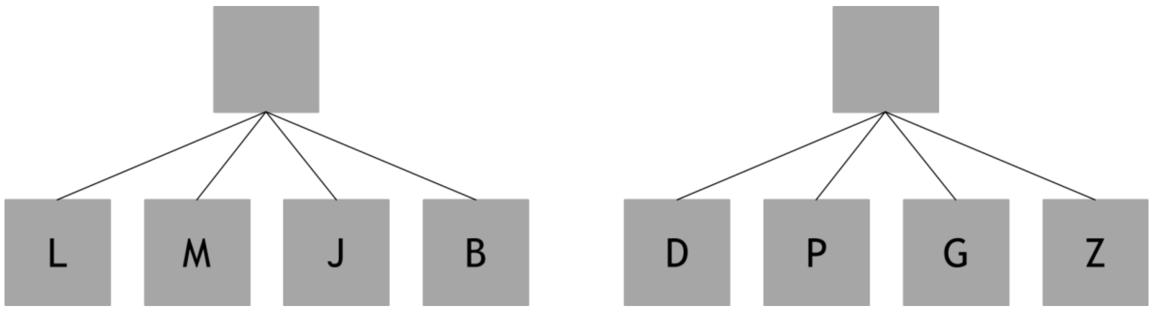
In a CN condition, participants have information and control at the element level, and only information at the bin level. They can only select the letter indicated within each group.

UC:



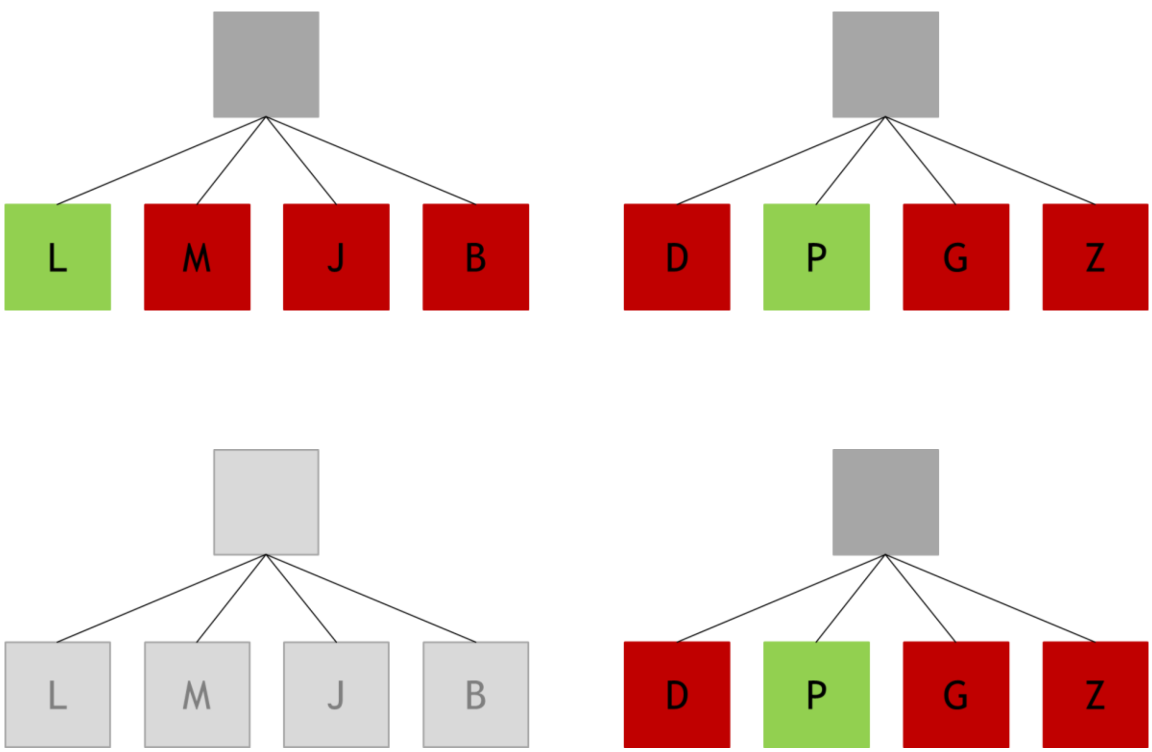
In a UC condition, participants have neither information or control at the bin level, but have information and control at the element level. They can select any letter in either group. Once they have made their selection, the group from which they selected would have its colours fade, indicating that no further selections are available from this group. In the example above, let us assume J was selected in the first group. The participants would then make a letter selection from the other group (P for example) and the letter assigned would be randomly chosen between both letter selections (50-50 chance of either J or P). This is indicative of the participants having either group assigned to them at random, with no information nor control.

UU:



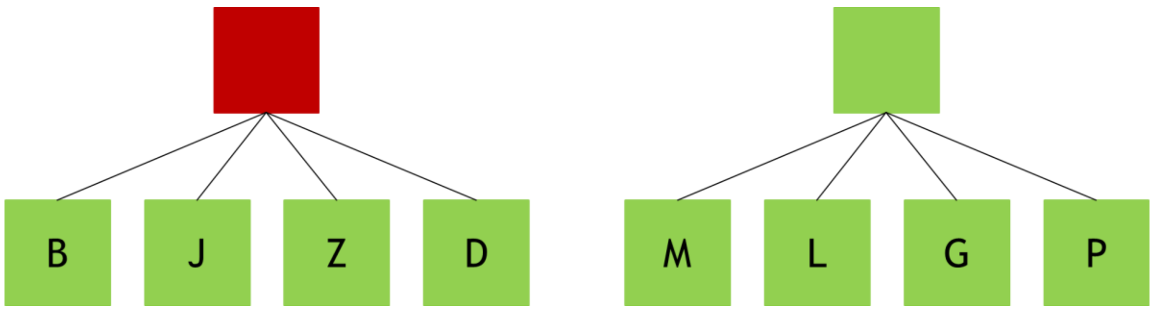
In a UU condition, participants have neither information or control at the bin or element levels. They can select any letter, but are assigned one of the eight randomly.

UN:



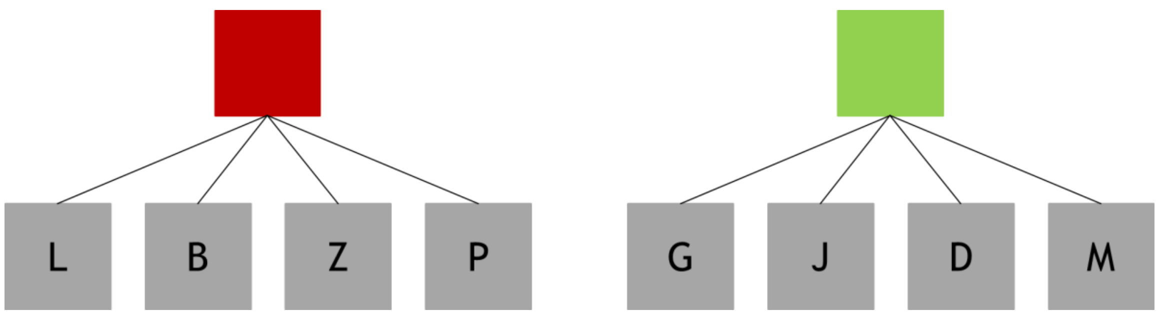
In a UN condition, participants have neither information or control at the bin level and only information at the element level. They can select each letter indicated within each group and are assigned either at random.

NC:



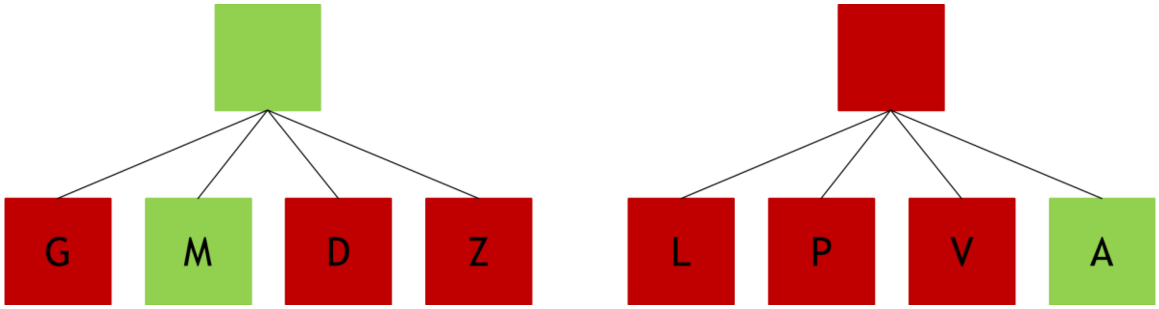
In a NC condition, participants have information, but not control at the bin level and information and control at the element level. They can select any letter within the group indicated as accessible, but are not able to select letters from the other group.

NU:



In a NU condition, participants have only information at the element level and neither information or control at the bin level. They can select any letter within the group indicated, but the letter assigned to them is random within that group.

NN:



In a NN condition, participants have only information at both the element and bin levels. They can only select the letter indicated to them.

Curriculum Vitae

Name:	Bryan Grant
Post-secondary:	University of Ottawa
Education and Degrees:	Ottawa, Ontario, Canada 2004-2010 B.Sc.
Honours and Awards:	Canada Graduate Scholarship – Master's Program (CGS-M) 2015-2016
	Western Graduate Research Scholarship (WGRS) 2014-2016
	Canada Graduate Scholarship – Doctoral Program (CGS-D) Doctoral Scholarship (SSHRC) To be awarded 2016-2019
Related Work Experience:	Research Assistant Children's Hospital of Eastern Ontario (Mental Health) 2010-2014
	Teaching Assistant The University of Western Ontario 2014-2016

Publications:

Smith, D.M., Grant, B., Fisher, D.J., Borracci, G., Labelle, A., Knott, V. (2013). Auditory verbal hallucinations in schizophrenia correlate with P50 gating. *Clinical Neurophysiology*, *124* (7), 1329-35.

Fisher, D.J., Grant, B., Smith, D.M., Knott, V.J. (2012). Nicotine and the hallucinating brain: effects on mismatch negativity (MMN) in schizophrenia. *Psychiatry Research*, *196* (2-3), 181-187.

Fisher, D.J., Grant, B., Smith, D., Borracci, G., Labelle, A., Knott, V. (2011). Effects of auditory hallucinations on the mismatch negativity (MMN) in schizophrenia as measured by a modified 'optimal' multi-feature paradigm. *International Journal of Psychophysiology*, *81* (3), 245-251.

Fisher, D.J., Grant, B., Smith, D.M., Knott, V.J. (2011). Effects of deviant probability on the 'optimal' multi-feature mismatch negativity (MMN) paradigm. *International Journal of Psychophysiology*, *79*, 311-315.

Villeneuve, C. M., Grant, B., Smith, D., Fisher, D. J., Labelle, A., & Knott, V. J. (2010). The effects of acute nicotine administration on electrocortical arousal in patients with schizophrenia. *International Journal of Psychophysiology*, *77* (3), 253-253.